SUPPLEMENTAL APPENDIX

Entry and Competition in Insurance Markets: Evidence from Medicare Advantage

Matthew V. Zahn*

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A Data and Sample Construction

In this section, I provide detailed descriptions of the data sets I use in my analysis and how the analysis samples for the demand and utilization estimates are formed.

A.1 Data Sources

My analysis relies on 11 data sources. A description of each data source and how it is used within my analysis appear below.

Medicare Beneficiary Summary File. This data set contains individual level information on all beneficiaries in the Medicare program. I observe the beneficiary's demographics such as age, sex, dual eligible status, reason for Medicare eligibility, and date of death. I can also track the beneficiary's county of residence in each month they were enrolled in Medicare. I also observe how the beneficiary opted to receive Medicare benefits (i.e., through Traditional Medicare or Medicare Advantage). If the beneficiary enrolled in Medicare Advantage, I observe the contract and plan identifiers for their chosen plan. I can also observe information about Medicare Part D plans but I do not use this information as part of my main analysis. I have access to these data from 2014–2019. The Beneficiary Summary File is used to construct market shares and demographics, as well as provide the observable characteristics of individuals in the demand and utilization models.

This data set also contains aggregate information about healthcare utilization and spending by category (e.g., inpatient, outpatient, etc.) for Traditional Medicare beneficiaries. I opt not to use this information because I am unable to construct the standardized utilization metric for this roll up of each beneficiaries claims. As a result, I would not have a consistent utilization metric for Traditional Medicare and Medicare Advantage beneficiaries. I do use this information to inform my calibration of the cost structure for Traditional Medicare that

*Department of Economics, Johns Hopkins University; matthew.zahn@jhu.edu.

appears in the utilization model.

Traditional Medicare Claims. This data set contains information about the utilization of healthcare among Traditional Medicare beneficiaries at the claim level. I have access to TM claims and discharges for inpatient, outpatient, carrier, hospice, and Part D services with differing levels of coverage. I observe 100% of inpatient and hospice claims as well as inpatient, outpatient, carrier, and Part D claims for a 20% random sample of TM beneficiaries each year. I have access to these data from 2014–2019. My analysis focuses on inpatient, outpatient, and carrier claims. These claims data are used for three purposes. First, I use them recover diagnoses for the risk score calculation. Second, they are used to construct the standardized price measure developed by Jung et al. (2022). Third, I use them as part of the utilization moments to estimate the parameters of the health state distribution and hassle costs of healthcare utilization.

Medicare Advantage Encounter Data. This data set contains information about the utilization of healthcare among Medicare Advantage beneficiaries at the encounter level. Unlike traditional claims data sets, the encounter data contain no payment information but do contain most other fields found in these sources. I have access to MA encounter data for inpatient (hospitals and SNFs), outpatient, carrier, hospice, and Part D services with differing levels of coverage. I observe 100% of inpatient, outpatient, and hospice encounters; all encounters for a cohort of 12 million MA beneficiaries (roughly 50–60% of the entire MA population depending on the year) which covers roughly 52% of MA beneficiaries in my analysis sample; and 20% of Part D encounters. I have access to these data from 2016–2018. The encounter data are used for four purposes. First, I use them to recover diagnoses for the risk score calculation. Second, I apply the standardized price measure developed by Jung et al. (2022), which I discuss in more detail below. Third, I use them as part of the utilization moments to estimate the parameters of the health state distribution and hassle costs of healthcare utilization. Fourth, I use average plan level utilization to recover the plan's negotiated prices along with the inversion of the plan's first order condition.

Medicare Advantage Bid Templates. This data set contains the information MA plans provide to CMS as part of the regulatory process that determines their subsidy and rebate payments. I have access to these submissions for every MA plan from 2006–2018 and they are publicly available on the CMS website. From this data source I recover the subsidy amount the plan requested, the size of its rebate payment, how its rebate was allocated, and the amount of revenue the plan needs to fund extra benefits relative to Traditional Medicare.

They also report how plan's premium is broken out between the base and supplemental premium. The bid templates also detail the numerical values of the cost sharing characteristics of the plan as well as their projected allowed amounts for medical claims. These data are used in three places within my analysis. First, I rely on them as part of inverting the plan's first order condition to recover the plan's negotiated prices. Second, I use them when estimating the size of a plan's supplemental premium. These data are also used to inform my calibration of the plan out-of-pocket cost functions that are used in the utilization model.

Medicare Advantage Enrollment. This data set tracks monthly county-level enrollment for all Medicare Advantage plans. The data also contain information about plan characteristics including network type and whether the plan is a special needs plan. I have access to these data from 2006–2019 and they are publicly available on the CMS website. These data provide characteristics of Medicare Advantage plans that appear as part of the demand, utilization, and fixed cost models and are used to determine the analysis sample.

Plan Benefit Packages. This data set tracks characteristics for Medicare Advantage plans. The tracked characteristics include the plan's premium, the counties included in the plan's footprint, and how the counties within a plan's footprint map to segment identifiers specific to the plan. I have access to these data from 2006–2019 and they are publicly available on the CMS website. These data provide characteristics of Medicare Advantage plans that appear as part of the demand model and are used to determine the analysis sample.

Out-of-Pocket Cost Estimates. This data set provides estimates for a beneficiary's expected out-of-pocket costs in Medicare Advantage plans and Traditional Medicare. These estimates are produced annually for every MA plan and TM and are typically featured on the Medicare plan finder application. The estimates are available for discrete health statuses ranging from "Poor" to "Excellent." The estimates are generated from a CMS developed model that takes the characteristics of MA plans, behavioral assumptions about how care is received (i.e., in-network), and utilization patterns from TM data for the plan's enrollee population. Cost estimates are produced for specific services (e.g., inpatient hospital acute care, eye exams, hearing exams, etc.) and may be aggregated up accordingly. I have access to these data from 2007–2020. I obtained these materials through a Freedom of Information Act request and direct correspondence with CMS staff. These data provide characteristics of MA plans and TM that are relevant for the utilization and demand models as well as estimating the size of a plan's supplemental premium.

Plan Ratings. This data set provides the star ratings used to denote the quality of a MA plan. I have access to these data from 2007–2020 and they are publicly available on the CMS website. These data provide characteristics of MA plans that are relevant for the demand model and estimating the size of a plan's supplemental premium.

Plan Payments and Ratebooks. These data sets contains information on plan level payments, rebates, and risk scores as well as the benchmarks set by CMS. I have access to these materials from 2006–2019 and they are publicly available on the CMS website. These data are primarily used when solving the model for counterfactual entry patterns and assessing the validity of the risk scores I calculate.

Medicare Geographic Variation. These data contain information on the Medicare program and its beneficiaries at the county-level. I have access to these materials from 2007–2019 and they are publicly available on the CMS website. These data are primarily used as a diagnostic to test the validity of the risk scores I calculate.

DRG InterStudy. This data set contains estimated enrollment for all insurance companies at the county level. The enrollment estimates are broken out by insurance product type (i.e., commercial-HMO, commercial-PPO, Medicare Advantage, Medicaid managed care, etc.). I have access to these materials for 2015, 2017, and 2019. These data are used to estimate the identified set of parameters in firm fixed costs.

AHA Annual Survey and Area Health Resources Files. These data sets contains information about the number of providers (e.g., hospitals, hospital systems, doctors, etc.) and utilization of healthcare services at the county level. These data are available with different time coverage but cover the period from 2007–2018. The Area Health Resource Files are publicly available on the Health Resource Service Administration. These data are used to estimate the identified set of parameters in the firm fixed costs. I obtained the AHA data from the Wharton Research Data Services.

American Community Survey. This data set contains demographic information at the county level. Specially, I use these data to measure mean and median income, household size, educational attainment, and what percentage of a county is rural. These data are publicly available on the Census website. These materials are used within the demand model.

A.2 Demand Sample

The sample used to estimate the demand model combines most of the data sets described in the previous section. The main file is the Medicare Beneficiary Summary File, which is then supplemented with data sets that contain the characteristics of Medicare Advantage plans and local markets. The end result is a panel of Medicare beneficiaries from 2017–2018. The sample also relies on information from the 2016. The sample restrictions based on individual characteristics are detailed below.

1. Individuals that do not qualify for Medicare because of their age. This condition means that beneficiaries that were not 65 by end of the sample year or were eligible for Medicare due to disability status or having End Stage Renal Disease are dropped.

2. Individuals that were enrolled in Medicare Part A for a different number of months within a year than they were enrolled in Medicare Part B. This pattern primarily arises because enrollment in Medicare Part A is automatic while beneficiaries must opt into Part B. A beneficiary may delay enrolling in Part B if they are still working and have employer sponsored coverage.

3. The beneficiary resides in Alaska, Guam, Puerto Rico, or the Virgin Islands. The Medicare program has idiosyncratic differences in these geographies.

4. The beneficiary has an invalid or missing geographic identifier.

5. The beneficiary is missing data needed to calculate their risk score.

I further restrict the sample based on Medicare Advantage enrollees and plans.

1. The beneficiary is enrolled in a MA plan with missing characteristic information (i.e., bids, out-of-pocket costs, payments, etc.).

2. The beneficiary is enrolled in an employer sponsored, special needs, or Part B only MA plan.

3. The beneficiary is enrolled in a plan outside of the plan's official footprint. This pattern can occur if an individual previously resided in a plan's footprint but relocated to a new geography and retained their MA plan.

4. The individual is enrolled in a plan type other than a HMO or Local PPO. Other types of MA plans in the data include Private Fee-For-Service (PFFS) or Regional PPOs, which either have different subsidy regulations, small enrollment, or distinct cost structures. HMOs and Local PPOs enroll the vast majority of MA beneficiaries.

The net result of these restrictions is a sample that contains 73,941,784 beneficiary-year observations and 40,141,182 unique beneficiaries. The sample contains 3,702 plan-year observations of 2,263 unique MA plans. See Appendix Table E.1 for a detailed breakdown of the number of observations that dropped due to each sample restriction.

A.3 Utilization Sample

This section describes the utilization sample. This discussion includes how I construct the utilization metric applied to the Medicare Advantage encounter data and check them for data completeness. I conclude by describing precisely how the encounter data are used to estimate the model.

Utilization Measure Construction. I implement the algorithm proposed by Jung et al. (2022) to generate the standardized price utilization metric. At a high level this procedure generates these standardized prices based on Traditional Medicare claims data by netting out price differences attributable to geographic variation and applies them to services that appear in the Medicare Advantage encounter data. As part of their publication, the authors provide SAS code and an implementation guide that other users can modify to implement the algorithm based on the data they have available from CMS. I make two adjustments to the procedure proposed by Jung et al. (2022). First, I define the MA cohort to include all beneficiaries. Second, I use data from all available Traditional Medicare beneficiaries to construct the standardized prices. In both instances the written procedure used randomly drawn sub-samples to ease computation burdens. I relax these requirements to make use of all available data resources.

Data Completeness. The implementation in Jung et al. (2022) provides methods to assess the completeness of the Medicare Advantage encounter data. The first compares the number of hospitalizations that appear in the inpatient encounter files against those that appear in the MedPAR files. The second compares the number of emergency department and ambulatory care visits that appear in the encounter outpatient and carrier files against information that appears in the Healthcare Effectiveness Data Information System (HEDIS).

I consider a Medicare Advantage contract to have a high degree of data completeness if it has at least 2,500 enrollees, the difference between the number of hospitalizations in the encounter and MedPAR data is less than 10%, and the number of ambulatory or ED visits in the encounter and HEDIS data are within 20%.

The contacts that I identify as having a high degree of completeness overlaps with the list reported in Jung et al. (2022). I have fewer contracts than they do because I only have access to a cohort of the carrier encounter data. Thus, the utilization sample is composed of Traditional Medicare beneficiaries included in the 20% random sample defined by CMS and all Medicare Advantage beneficiaries enrolled in a plan associated with a contract that has a high level of data completeness. Beneficiaries in the random sample or a MA plan with high data completeness that are not observed in the claims or encounter data are assumed to have utilized no healthcare in that year.

Use in Estimation. The utilization sample is used to define the moments to target the parameters of the health state distribution and plan effects on individual utilization patterns. The model predicted utilization is also used to quantify the marginal costs of plans. This modeling choice is supported by evidence that documents Medicare Advantage plans paying similar prices as Traditional Medicare. Since utilization is measured in terms of standardized Traditional Medicare dollars, the model predicted utilization for a beneficiary also represents their marginal costs. I rely on these estimates when deriving the moment inequalities to recover the identified set of firm fixed costs.

A.4 Risk Score Calculation

CMS calculates risk scores for each beneficiary in the Medicare program. The general formula used in this calculation has three components and is reproduced below.

$$r_{it} = [\underbrace{R_{it}(\text{HCC Model}_t)}_{\substack{\text{Base}\\ \text{score}}} / \underbrace{NF_t}_{\substack{\text{TM}\\ \text{normalization}}}] \cdot 1\{\text{MA bene } t-1\} \underbrace{CPA_t}_{\substack{\text{Coding pattern}\\ \text{adjustment}}} \tag{A.1}$$

The first component is the base score, which is the output of the HCC models developed, maintained, and updated by CMS. Each version of the HCC model is publicly available on the CMS website. The HCC model takes a beneficiary's demographics (i.e., age, sex, Medicare eligibility, Medicaid eligibility, etc.) and diagnoses from the prior year as inputs. The diagnoses must be recorded from inpatient or outpatient hospital visits, physicians, or clinically trained non-physicians (e.g., psychologist, podiatrist). The HCC models return different base scores for different types of beneficiaries (e.g., new beneficiaries, dual eligibles, etc.).

The remaining parts of the formula modify the base score. The second component is a normalization factor. This adjustment is defined based on the costs and diagnoses of the Traditional Medicare population for a rolling reference period. The factor is calculated such that after it is applied to the base score, the average Traditional Medicare will have a risk score equal to one. The final component is a coding pattern adjustment that is intended to correct for "upcoding" among Medicare Advantage plans. The normalization factors and and coding pattern adjustments used by CMS are published as part of their ordinary course.

As discussed in the main text, these risk scores are generally not made available in the data sets usable for researchers. I approximate the CMS risk scores with the data available to me based on Equation (A.1). To calculate the base scores, I gather diagnoses from the TM claims and MA encounter data for the years 2016–2018.[1] I then feed these into the HCC models for the years in my analysis sample along with the beneficiary demographics from the Medicare Beneficiary Summary File. I define the average TM base score within each sample year as the formalization factor. After applying the normalization factors to the base scores, I apply the reported coding pattern adjustments to Medicare Advantage beneficiaries. I compute two versions of these risk scores: one that uses only inpatient diagnoses (which I have for all beneficiaries) and another that uses inpatient, outpatient, and carrier diagnoses in the data available to me.

B Model and Estimation

In this section I provide additional details about components of the model and its estimation that are not covered in the main text.

B.1 Healthcare Utilization

Plan Cost Structures and Utilization Solution. The amount of healthcare agents choose to utilize in my model depends on the out-of-pocket costs associated with that level of utilization in their chosen health plan. While the insurance products examined in this paper are complex and have many idiosyncrasies, I make two simplifying assumptions to preserve tractability. First, I assume that the amount of money a beneficiary in a MA plan or TM can be expressed as a function of the amount of healthcare the beneficiary chooses

[1] I exclude MA diagnoses generated from chart reviews.

to consume Q and (at most) three characteristics of the insurance contract: a deductible D, a coinsurance rate C, and an out-of-pocket maximum M. Second, I assume that there are only four out-of-pocket cost structures for Medicare Advantage plans—one for each network type and financial generosity category. I calibrate the cost structures for each Medicare Advantage plan and Traditional Medicare. The calibration for Medicare Advantage plans is informed by information included in the plan's bid template that is submitted to CMS. Among the information included in these materials are estimates for the dollar value of total cost sharing and allowed amounts for each beneficiary the plan enrolls. I take the ratio of these values to generate a pseudo-coinsurance rate for the plan. These templates also report the plan's out-of-pocket maxima and deductibles. The calibration for Traditional Medicare is informed by statues.[2] Table B.1 reports the calibrated cost functions as well as the analytical expression for the optimal amount of healthcare to consume within each plan.

Table B.1: Calibrated out-of-pocket cost functions and predicted healthcare utilization

	HMO		Local PPO		TM
	High	Low	High	Low	
Deductible D	\$0	\$1,000	\$500	\$2,000	\$1,500
Coinsurance C	6%	10%	8%	10%	20%
Out-of-pocket maximum M	\$3,500	\$6,000	\$5,000	\$7,000	NA
$Q^* > 0$	$h > \bar{h}$				
$Q^* = h$	NA	$h \leq \min\{\bar{h}_1, \bar{h}_2\}$			$h \leq \bar{h}_1$
$Q^* = h(1+\omega(1-C))$	$h \leq \bar{h}_2$	$h \in (\bar{h}_1, \bar{h}_2)$ & $\bar{h}_1 < \bar{h}_2$			$h > \bar{h}_1$
$Q^* = h(1+\omega)$	$h > \bar{h}_2$	$h \geq \max\{\bar{h}_1, \bar{h}_2\}$			NA
$\bar{h}_1$	$2D/(2+\omega(1-C))$				
$\bar{h}_2$	$2(M-D(1-C))/(2C(1+\omega)-C^2\omega)$				
$\bar{h} = \begin{cases} \bar{h}_{01} & \text{if } \bar{h}_{01} < \bar{h}_1 \text{ else} \\ \bar{h}_{02} & \text{if } \bar{h}_{02} < \bar{h}_2 \text{ else} \\ \bar{h}_{03} & \text{else} \end{cases}$	$\bar{h}_{01} = 2\omega\phi$				
	$\bar{h}_{02} = 2\omega(D(1-C)+\phi)/(1+\omega(1-C)^2)$				
	$\bar{h}_{03} = 2\omega(M+\phi)/(1+\omega)^2$				

Notes: This table summarizes the calibration of the out-of-pocket cost functions and the analytical solution for healthcare utilization for each plan type within the model.

These calibrations align with stylized facts about Traditional Medicare and Medicare Advantage plans. In general, Traditional Medicare tends to have higher costs because of

[2]For 2017–2018 the TM deductible for outpatient care was \$183 and a 20% coinsurance. For inpatient care, TM charges a per-hospitalization deductible which was approximately \$1,300 dollars for 2017 and 2018. An examination of the Cost and Use component of the Medicare Beneficiary Summary File for Traditional Medicare beneficiaries during this time period indicates that the average TM beneficiary that utilized inpatient care paid about this amount out-of-pocket.

coverage gaps and no out-of-pocket maximum. This pattern is what drives many Traditional Medicare beneficiaries to supplement their coverage with additional insurance policies like Medigap. Part of Medicare Advantage's value proposition is that it tends to have lower out-of-pocket costs relative to Traditional Medicare because it fills those coverage gaps. HMOs tend to have lower costs relative to PPOs, which is reflected in the calibration. However, HMO plans tend to have stricter measures in place that enrollees have to clear before utilizing care the plan will cover (i.e., referrals and prior authorization). These additional steps Medicare Advantage plans take to reduce utilization among their enrollees is captured by the plan-type component included in the hassle cost of utilizing care.

The middle panel of Table B.1 reports the analytic solution for the optimal amount of healthcare for a beneficiary to consume. These expressions depend on an individual's health state h_{it}, moral hazard parameter ω_i, and plan choice. These expressions have intuitive interpretations. Given the hassle costs of utilizing care ϕ_{ijt} an individual must have a sufficiently large health need to justify consuming a positive amount of healthcare. These hassle costs also capture measures MA insurers may use to limit the amount of care their beneficiaries consume. Once this health threshold is met, individuals in plans with a deductible face a marginal cost of one and will consume healthcare at that rate. As health needs grow and the beneficiary approaches their deductible amount, their utilization will jump beyond their deductible in anticipation of the lower marginal cost of consuming care due to the cost sharing with coinsurance. This behavior induces them to consume healthcare above their health state, which is traditionally interpreted as moral hazard spending and is partially mitigated by cost sharing. Similar logic applies for the discontinuity MA beneficiaries face as they approach their plan's out-of-pocket maximum. After reaching $\bar{h}_2$ spending discontinuously jumps to consume the full amount of care informed by their health state and moral hazard parameters, consistent with the fact that the marginal cost of care at this point is zero. The final item to note is that if the size of the coinsurance region for a plan is small relative to a beneficiary's moral hazard parameter, it is optimal for them to immediately jump from the deductible region to the out-of-pocket maximum region.

Computing Q^*_{ijt} for a given set of model parameters requires integrating over the unobserved heterogeneity in the health state distribution. I employ quadrature to handle this integration in a relatively simple manner. I use nine nodes (n_s) to approximate the joint distribution of the observable component of health state distribution mean and the moral hazard parameter ($\bar{\mu}, \log \omega$). These nodes and associated weighting matrix are denoted by d_s and W_s respectively.

For a given s node, I can evaluate draws from the health state distribution. Notice:

$$\begin{bmatrix} \bar{\mu}_{its} \\ \log \omega_{is} \end{bmatrix} = \begin{bmatrix} \mathbf{X}^{\mu}_{it} \boldsymbol{\beta}^{\mu} \\ \mathbf{X}^{\omega}_{i} \boldsymbol{\beta}^{\omega} \end{bmatrix} + d_s \cdot \text{chol} \left(\begin{bmatrix} \sigma^2_{\mu} & \\ \sigma^2_{\mu,\omega} & \sigma^2_{\omega} \end{bmatrix} \right) \tag{B.2}$$

where "chol" denotes the Choleksy decomposition of the variance covariance matrix. I use 27 nodes (n_b) to approximate the health state distribution, whose nodes and weighting matrix are denoted by d_b and W_b. Thus for a given set of model parameters and s and b nodes the health state for an individual is:

$$h_{itsb} = \exp(\bar{\mu}_{its} + d_b \underbrace{\mathbf{X}^{\sigma}_{it} \boldsymbol{\beta}^{\sigma}}_{=\sigma_{h,it}}) \tag{B.3}$$

From here it is straightforward to compute the node specific optimal healthcare utilization $\hat{Q}^*_{ijtsb}$ and apply the quadrature weights to integrate over the health state distribution:

$$\hat{Q}^*_{ijts} = \sum_{b=1}^{n_b} W_b \cdot \hat{Q}^*_{ijtsb} \tag{B.4}$$

Agents make the healthcare utilization decision conditional on their plan choice. Thus, the node specific optimal healthcare utilization $\hat{Q}^*_{ijts}$ must be weighted by the node specific probability the individual enrolled in plan j, which is denoted by s_{ijmts}. After weighting $\hat{Q}^*_{ijts}$ by the choice probabilities, I apply quadrature to integrate out the remaining unobserved heterogeneity and recover $\hat{Q}^*_{ijt}$:

$$\hat{Q}^*_{ijt} = \sum_{s=1}^{n_s} W_s \cdot s_{ijmts} \cdot \hat{Q}^*_{ijts} \tag{B.5}$$

B.2 Plan Choice

Agents in the model pick the Medicare Advantage plan (or Traditional Medicare) from their plan menu $\mathcal{J}_{mt}$ that maximizes their expected utility. The expectation is taken over the distribution of their future health state. Calculating choice probabilities from this model present two challenges. The first is the double exponentiation introduced by the CARA utility function and the second is integrating over the unobserved heterogeneity in the health state distributions. To address the former and avoid numerical issues, I follow Marone and Sabety (2022) and use certainty equivalent utility to construct choice probabilities, while quadrature is used to integrate the unobserved heterogeneity. Thus, for a given set of model parameters and s node an individual certainty equivalent utility for plan j is (U^{CE}_{ijmts}):

$$U^{CE}_{ijmts} = \bar{l}_{ijmts} - \frac{1}{\psi} \log\left(\sum_{b=1}^{n_b} W_b \cdot \exp[-\psi(l_{ijmts}(h_{itsb}) - \bar{l}_{ijmts})]\right) \tag{B.6}$$

where $\bar{l}_{ijmtsz} = \mathbb{E}_h[l_{ijmtsz}(h_{itszb})]$. Given the assumptions on ϵ_{ijmt}, the node specific choice probabilities take the logit form. Applying quadrature integrates out the unobserved heterogeneity:

$$s_{ijmts} = \frac{\exp(U^{CE}_{ijmts})}{1 + \sum_{\ell \in \mathcal{J}_{mt}} \exp(U^{CE}_{i\ell mts})} \tag{B.7}$$

$$s_{ijmt} = \sum_{s=1}^{n_s} W_s \cdot s_{ijmts} \tag{B.8}$$

Finally, market shares s_{jmt} are obtained by integrating over the population of individuals within the market. Let W_{imt} and M_{mt} denote the weight on each individual in market and the market size. Market shares are computed as:

$$s_{jmt} = \sum_{i=1}^{M_{mt}} W_{imt} \cdot s_{ijmt} \tag{B.9}$$

B.3 Subsidy Choice and Unobserved Costs

In this section, I provide additional details about service areas and how I recover unobserved MA plan costs. Defining service areas is important to determining the set of direct and indirect competitors for MA plans. Unobserved plan costs are important to capture as my healthcare utilization metric does not include all potential claim/encounter types and does not capture non-utilization based costs associated with enrollment.

Service area definition. The geographic space where Medicare Advantage plans compete are called service areas. Service areas are defined at the state level. For larger states like California, Texas, and Florida, service areas are subsets of counties within the state based on commonly understood geographic boundaries (i.e., South Florida, West Texas, Southern California, etc.).

Observed entry patterns of plans largely align with these service area definitions. For the plans with an observed footprint that spans multiple service areas, I assign them to their primary service area where the plurality of their enrollees are located. For purposes of estimating the model, these plans make endogenous decisions within their primary service area but are taken as exogenous players in the other service areas where they are present.

Recovering unobserved costs. I used data on MA plan margins to recover unobserved costs. Given these data and my parameter estimates for the health state distribution and consumer demand, I solve Equation (10) analytically for λ_{jt}.

B.4 Stage 2 Estimation

This section describes the moments used to estimate the Stage 2 parameters of the model as well as the estimation algorithm.

To estimate the Stage 2 parameters I use the general method of moments. The overall procedure resembles a micro-BLP application and follow many of the best practices recommended by Conlon and Gortmaker (2023).

Let $\mathcal{M}(\theta)$ denote the vector of moment equalities that target healthcare utilization patterns and the IV restriction and depends on the model's parameters. I search for the parameter vector $\theta = \{\theta_1, \theta_3\}$ that solves:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{M}(\theta)' \mathcal{W} \mathcal{M}(\theta) \tag{B.10}$$

where $\mathcal{W}$ is a positive definite weighting matrix.

I first obtain an initial estimate for the optimal weighting matrix $\hat{\mathcal{W}}$ based on initial guesses for θ that fits the moments reasonably well. Given this estimate for $\hat{\mathcal{W}}$ I search for the parameter vector $\hat{\theta}$ which solves Equation (B.10). Once this process converges, I update my estimate for the optimal weighting matrix and repeat the search process. After the two-step estimation procedure is complete I obtain standard errors using the standard formula for the variance-covariance matrix of the GMM estimator.

Below is a description of the steps in the estimation algorithm for a candidate θ.

1. Compute the health state realizations h_{itsb} given the candidate parameter vector.

2. Compute the relevant quantities from the health state distribution to construct the model moments. These calculations are done for each category of observable heterogeneity c in each plan network-generosity type and the outside option.

3. Compute the utilization stage utility (see Equation (2)) for each health state realization. This requires recovering the out-of-pocket costs associated with the model

implied Q^*_{ijtsb} for each plan choice type in the model. Hassle costs are recovered given the a candidate parameter vector.

4. For each market m:
   (a) Recover the mean utility parameter δ_{jmt} using the Berry et al. (1995) contraction mapping that allows model predicted plan-level market shares to match their data analogs (i.e., $\hat{s}_{jmt}(\delta, \theta) = s_{jmt}$). I use the SQUAREM algorithm proposed by Varadhan and Roland (2008) to speed up the convergence of this fixed point.
   (b) Use the model choice probabilities to construct the model predicted healthcare utilization and plan choice moments for the individuals in the market.
5. Recover the demand residual ξ_{jmt} for the IV moment using the 2SLS formula.
6. Compute the moments in $\mathcal{M}(\theta)$ and evaluate the objective function in Equation (B.10).

The estimates for θ_2 are recovered post-estimation using the formula for the 2SLS estimator with the values for δ_{jmt} associated with the $\hat{\theta}$ estimates as the dependent variable. Estimates for θ_4 are recovered from the auxiliary regression in Equation (13). Given these parameters estimates, I can recover the empirical distribution of the demand and efficiency shocks $e = (\xi, \varepsilon_1, \varepsilon_2)$, which are used when deriving the moment inequalities.

B.5 Stage 1 Moment Inequality Derivation and Inference Details

Derivation. This section provides additional technical details related to the derivation of the moment inequalities used to estimate the parameters in Stage 1 of the model. As discussed in the main text, firms are endowed with CMS contracts that determine all possible plans the firm may offer in a service area. These contracts are network type specific and all plans offered under the contract have the same provider network and quality rating. Given this structure deviations from the observed decisions have a product characteristic and geographic component.

Let's first consider the characteristic deviations within a single market. To fix ideas, suppose we observe a firm with an HMO contract that entered plan j in market m as a low generosity HMO. There are two possible deviations to consider: plan j could have entered as a high generosity HMO or the firm could have also offered a second plan k as a high generosity HMO in the market alongside j.[3] If a firm is observed to hold both HMO and PPO contracts within the service area, then same logic generates 14 possible deviations relative to the observed equilibrium.[4]

Now we can add the geographic component of the deviations. Let's further suppose that the service area in question has only four counties. For the firm with only an HMO contract there are 4,094 possible deviations where they enter at least one market and offer at least one product.[5] By the same logic, for a firm with an HMO and PPO contract there are over 1.15e18 possible deviations. Thus it is necessary to place restrictions on the types of deviations that are permissible to maintain tractability.

I start this process by defining the competitively relevant firms within a service area. A firm falls into this category if the share of MA beneficiaries it enrolls within its primary service area is greater than 5%. Firms that do not meet this threshold comprise the competitive fringe. These firms are not considered as part of the deviation sets and their decisions are taken as exogenous when solving the counterfactual equilibria. Next I define similar plan pairs among the competitively relevant firms. Two plans are considered similar if they are offered in the same service area, have the same network type and generosity level, star ratings within half a point, and a premium within a single standard deviation. For each plan in the similar plan pair, I iteratively simulate adding or removing the plan for each market within the service area holding fixed decisions about other markets and the choices of other firms. This process involves computing a firm's expected profits over the distribution of the demand and efficiency shocks $e = (\xi, \varepsilon_1, \varepsilon_2)$. I take draws from this empirical distribution, compute the equilibrium given these draws, and average over the draws to compute the firm's expected profits.

After simulating the observed and counterfactual equilibria for the competitively relevant plans, I account for selection bias. As discussed in the main text, I leverage assumptions on the structural shocks ν_2 to employ a two level differencing strategy. The first difference is within firm and isolates the change in variable profits from adding or removing a market from a plan's observed footprint (see Equation (23)). The second difference is across similar plan pairs, where the isolated variable profit deviations involving adjacent markets are subtracted (see Equation (25)). I obtain unbiased moment inequalities for estimation by

[3]In cases where the firm offers the high generosity plan HMO k in markets other than m this deviation is equivalent to saying that plan k also enters m.

[4]The 14 deviations arises from the $2^4 - 2$ possible configurations of 4 possible plan types where at least one plan is offered and one of the possible configurations is observed in data.

[5]This number arises from the fact that there are 4 possible markets with 3 possible plan offerings in each market. Thus there are $2^{12} - 1$ possible entry configurations where at least one market is entered and one of these configurations is observed, leaving 4,094 deviations.

averaging over all adjacent market deviations within a plan.

Inference. I construct estimates for the identified set of fixed costs parameters by inverting the test statistic in Chernozhukov et al. (2019) for their SN1 subvector inference procedure. This method is attractive because it requires no tuning parameters and has a closed form for critical values, which reduces its computational burden. As described in the main text, the test statistic is based on studentization of the moment inequalities. To illustrate how the test statistic is constructed, let D denote the total number adjacent market pairs for a plan. Let $m_j(\theta)$ denote the inequality that eliminated the selection bias for plan pair j (i.e., Equation (25)):

$$m_j(\theta) = \Delta^- F(m, m') - \Delta^+ \sum_{\mathcal{J}_A} \mathbb{E}\,\Pi(m, m') - \Delta^+ \nu_1(m, m') \leq 0 \tag{B.11}$$

The mean and standard deviations for moment k are:

$$\varphi_k = \frac{1}{D}\sum_{d=1}^{D} m_{kd}(\theta) \qquad \varsigma_k = \sqrt{\frac{1}{D}\sum_{d=1}^{D}(m_{kd} - \varphi_k)^2} \tag{B.12}$$

These values for each moment are used to compute the test statistics:

$$T = \max_{1\leq k\leq K} \frac{\sqrt{D}\varphi_k}{\varsigma_k} \tag{B.13}$$

which are then assessed against the critical value for significance level α:

$$c(\alpha) = \frac{\Phi^{-1}(1 - \alpha/K)}{\sqrt{1 - \Phi^{-1}(1 - \alpha/K)^2/D}} \tag{B.14}$$

I use the following procedure to invert the test statistics and construct the estimates for each subvector of the identified set.

1. Define a grid of 1,000 starting values for each parameter.

2. For each starting value in the grid minimize the test statistic until it falls just below the critical value.

3. Repeat for the entire grid of starting values for the parameter of interest.

4. Results from the optimization for each parameter represent the $1 - \alpha$ confidence set of

the identified set of fixed cost parameters.

C Additional Descriptive Analyses

C.1 Quantifying the impact of the ACA on benchmarks

The ACA directly altered both payments to Medicare Advantage plans. These changes were motivated in part to address concerns about over-payments to plans participating in the program. The ACA aimed to lower subsidy payments by lowering the TM cost benchmarks to better align them with realized TM costs and limit how they could grow over time. The ACA sought to lower rebate payments by reducing the allowable fraction of the difference between the subsidy and the cost benchmark.[6] In general, these reforms were successful in lowering the payments MA plans received, which I quantify later in this section.

The ACA reforms to benchmarks were phased in from 2012–2016. Counties were given 2, 4, or 6 year transitions based on how far their current benchmarks were from the targets mandated by the ACA.[7] Following the transition, a county's cost benchmark was equal to the government's projected TM costs for the county in the prior year. These projections were binned into quartiles and scaled by an adjustment factor.[8] The benchmarks plans face are enrollment weighted averages of each market specific benchmark across its footprint. These footprints are plan specific and do not perfectly overlap with the footprints of rival plans. Thus the variation in the benchmarks for other markets can act as a source of plausibly exogenous variation in plan subsidy and rebate payments that induces plans to offer more or less financial coverage in a particular market.

To quantify the size of these reductions I estimate models of the following form:

$$B_{mt} = \alpha_0 + \alpha_1 \text{Post-ACA}_{mt} + \alpha_2 X_{mt} + \epsilon_{mt} \tag{C.15}$$

where B_{mt} is the benchmark for county m in year t, Post-ACA$_{mt}$ is an indicator for whether county m completed its transition ACA benchmarks, X_{mt} is a vector of characteristics for county m in year t and ϵ_{mt} is a county-year unobserved characteristics. I exclude observations

[6] Despite aiming to reduce these payments, the ACA also introduced quality adjustments that increased benchmarks and allowable rebate fractions for plans with higher star ratings. These limited the size of the payment reductions for these types of plans.

[7] Changes to the rebate fraction were phased in from 2012–2013 and did not vary by county or plan type.

[8] Counties in the first quartile (lowest projected TM costs) were adjusted up by 15% and 7.5% in the second. Third quartile counties received no adjustment and the fourth quartile (highest projected TM costs) was adjusted down by 5%.

for county-years that were mid-transition. Benchmarks are inflation adjusted to 2008 dollars.

My estimates of Equation (C.15) are presented in Table E.2. I consider three different measures of county benchmarks: the average benchmark weighted by observed plan enrollment, the non-quality adjusted benchmark, and the quality adjusted benchmark. For each benchmark I estimated two versions of Equation (C.15): one that used only county and year fixed effects in X_{mt} and another that used county characteristics that are likely correlated with healthcare utilization.[9] Estimates from both specifications were similar.

Consistent with the legislation's objectives my estimates indicate Medicare Advantage benchmarks fell significantly following the ACA's implementation. The ACA lowered average benchmarks by approximately \$43–58 per-beneficiary-month or \$516–696 per-beneficiary-year. The benchmark reductions are much larger for plans that did not receive quality bonuses (approximately \$59–71 per-beneficiary-month or \$696–856 per-beneficiary-year) and much lower for plans that do receive quality bonuses (\$32–48 per-beneficiary-month or \$384–576 per-beneficiary-year). These estimates quantify the variation in MA benchmarks the ACA introduced. In the main text I use this variation to quantify the connection between these benchmarks and plan characteristics. While the equilibrium model cannot use this same ACA shock to benchmark due to data limitations, variation in benchmarks over time and across markets is used to separately identify private health information from moral hazard. This variation is also demonstrated in the main text of the paper.

C.2 ACA event studies

In the main text I describe how the ACA lowered cost benchmarks for Medicare Advantage plans. Counties were given 2, 4, or 6 years to transition to the new ACA benchmarks based on how far their current benchmarks were from the ACA targets. The phase in occurred from 2012–2016. I estimate a series of event studies that capture the impact of these changes to plan benchmarks altered Medicare Advantage market outcomes. The estimated event studies are of the following form:

$$Y_{mt} = \beta_m + \beta_t + \beta_0 B_{mt} + \sum_{i \in \{[2008,2017] \setminus 2011\}} \beta_i 1[t = i] B_{mt} + \epsilon_{mt} \tag{C.16}$$

Figures E.3–E.6 present the event study plots for models estimated by transition

[9] These characteristics include the share of the county classified as rural, the share of the county population with a college degree, median income in the county, the average age of the Medicare population in the county, the share of the population in the county that is white, the share of the county that is eligible for Medicaid, and realized per-capita TM costs.

groups. Pooled estimates are similar and available upon request. The plots indicate that the benchmark reductions led to significant reductions in the payments to HMO and PPO plans. This was driven by a significant decrease in the subsidies plans requested following the benchmark reductions. These declines in requested subsidies were associated with significant increases in MA plan premiums in some markets relative to before the year before the benchmark reductions came into effect. Despite these cuts in benchmarks, MA plans tended to increase the amount of extra coverage they offer relative to TM in each type of transition county. The reductions in benchmarks led to modest but statistically significant reductions in the number of MA firms, contracts, and plans offered in most markets. Finally, Medicare Advantage enrollment increased despite the benchmark reductions. This growth is most pronounced in 2 year transition counties.

D Counterfactual Analyses

To compute the counterfactual equilibria of the model in a tractable way, I follow the procedure proposed by Lee and Pakes (2009). This approach has been used by other papers that solve models with multiple equilibria (see e.g., Wollmann, 2018). The method is based on an iterative best response. The procedure for solving for the equilibrium plan menu in year t proceeds as follows:

1. Set the initial plan menu in each market to what was observed in year $t-1$ and endow the firms with a move order.

2. The first firm in the order best responds to $t-1$ plan menu.

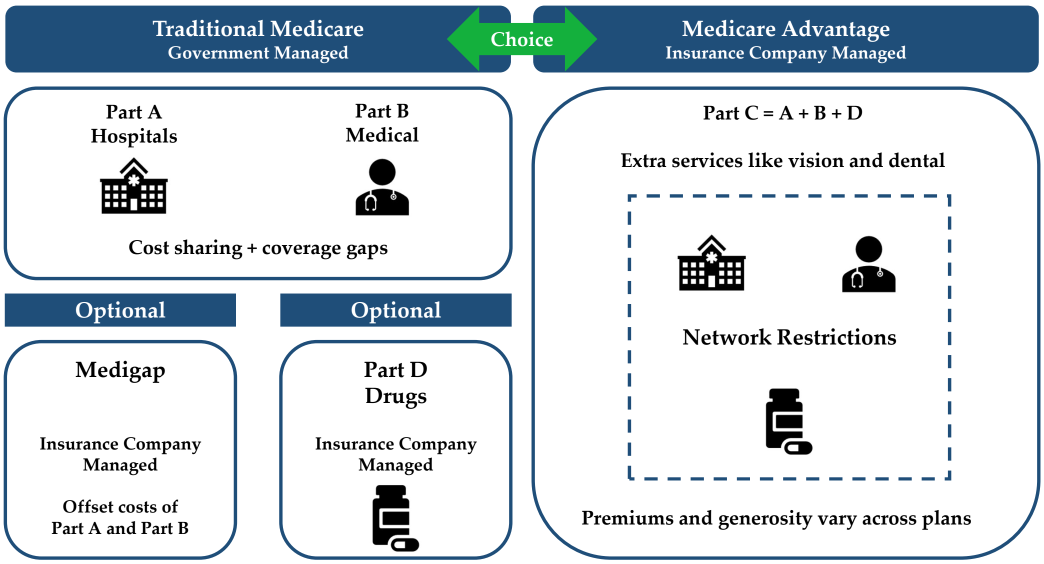
3. The second firm best responds to the $t-1$ plan menu that includes the first firm's best response. This process continues for each firm in the move order.

4. After all firms have play their best responses, the process returns to the first firm. The algorithm stops when all firms have played without changing their best response.

An equilibrium in this procedure will satisfy the Stage 1 necessary condition in Equation (17)) that was used to derive the moment inequalities. As a result the procedure will yield an equilibrium consistent with the simultaneous moves of firms in the model. The move order is determined by service area market shares in $t-1$.

E Additional Tables and Figures

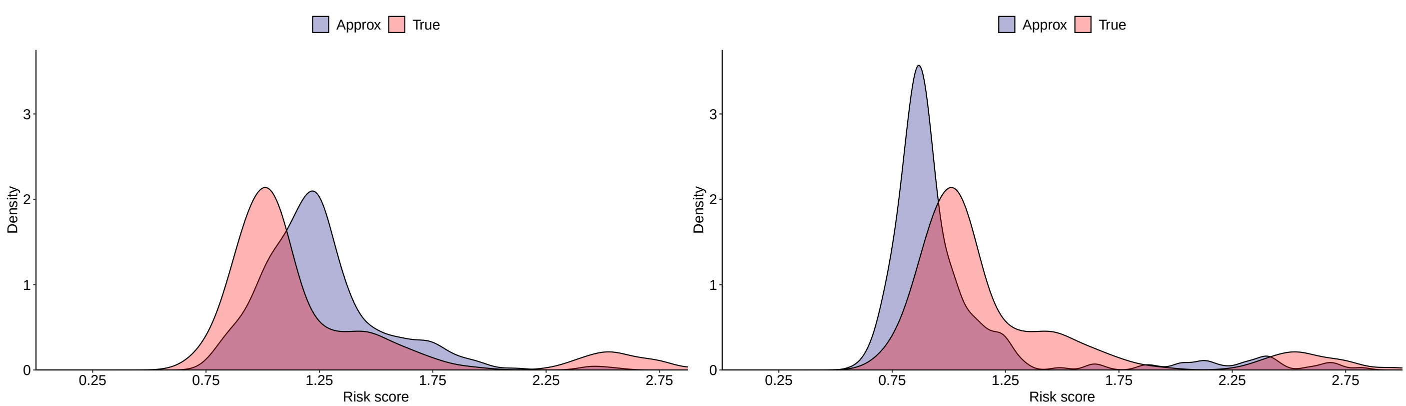
Figure E.1: Coverage choices in Medicare



Notes: This figure summarizes the choices and tradeoffs Medicare beneficiaries face when making their annual health insurance coverage decisions.

Figure E.2: Average plan risk scores, 2017–2018 (HMO and Local PPO)

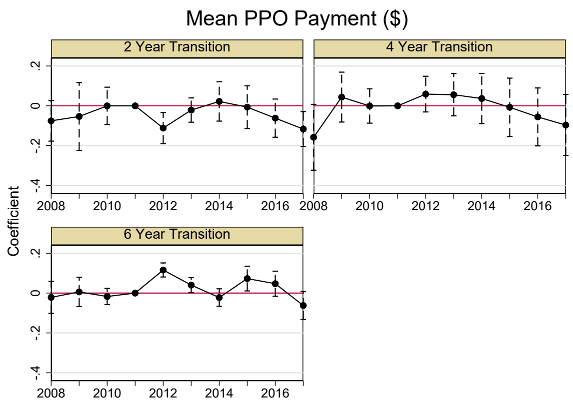
(a) IP, OP, and Carrier Diagnoses (b) IP Diagnoses



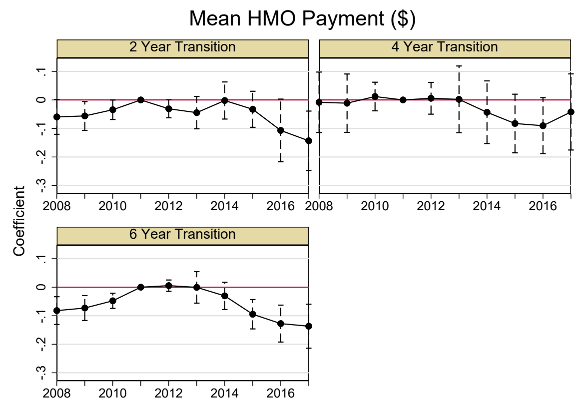
Notes: This figure compares the distribution of risk scores at the plan-level. The red distribution is the true risk score reported by CMS. The blue distribution comes from the risk scores that I calculate. The left panel uses diagnoses from inpatient, outpatient, and selected physician encounters and the right panel only uses inpatient diagnoses. These individual risk scores are averaged across all individuals in the MA plan to construct the distribution.

Figure E.3: ACA benchmark event studies: average plan payments, 2008–2017

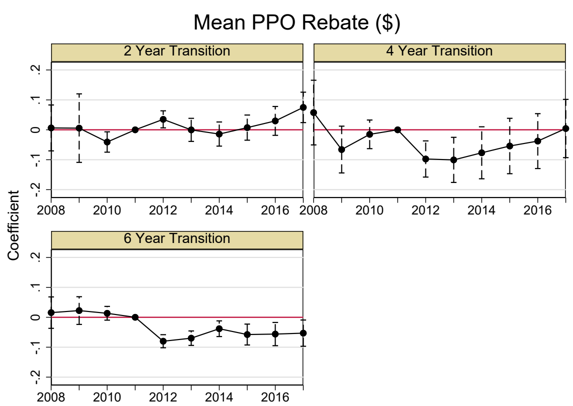
(a)



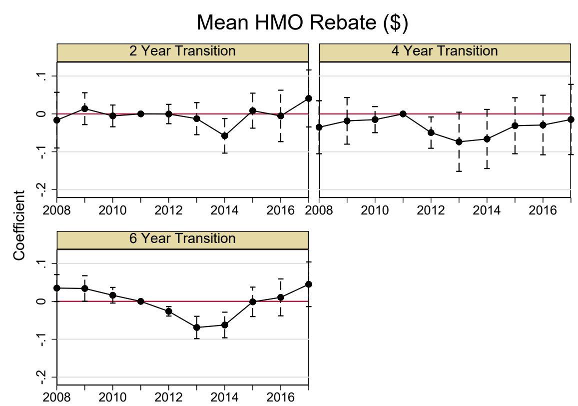
(b)



(c)



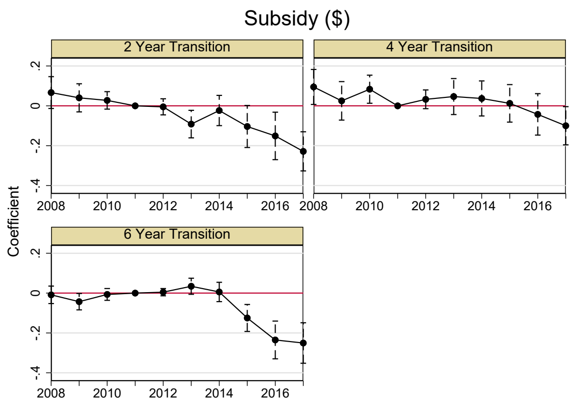
(d)



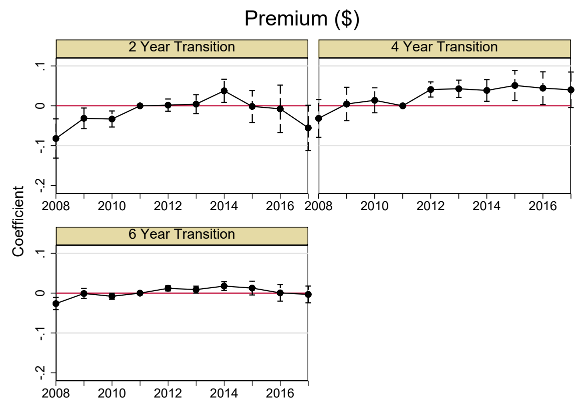
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on plan subsidy and rebate payments for HMO and PPO plans. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

Figure E.4: ACA benchmark event studies: average plan characteristics, 2008–2017

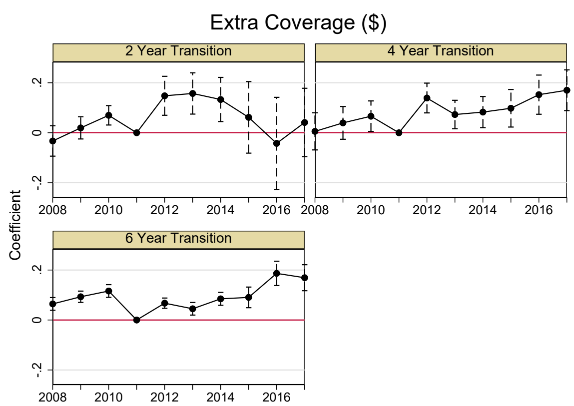
(a)



(b)



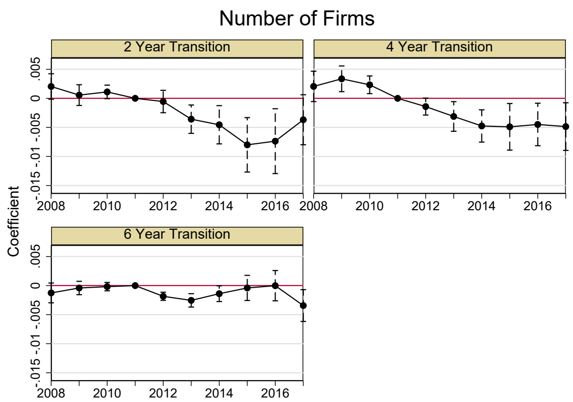
(c)



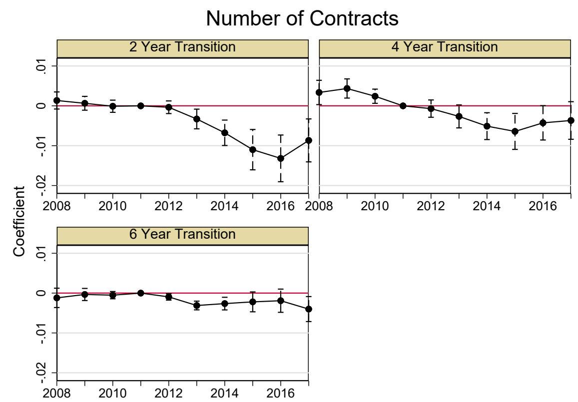
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on plan characteristics. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

Figure E.5: ACA benchmark event studies: average entry, 2008–2017

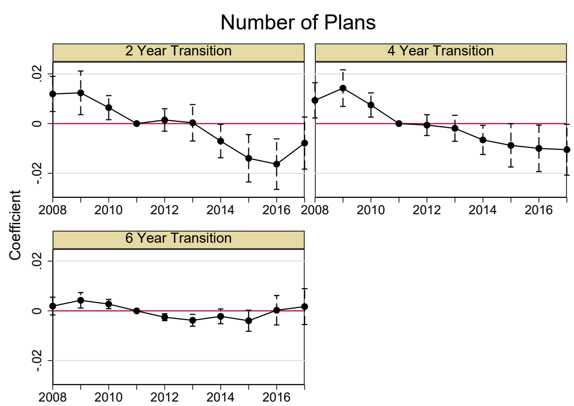
(a)



(b)



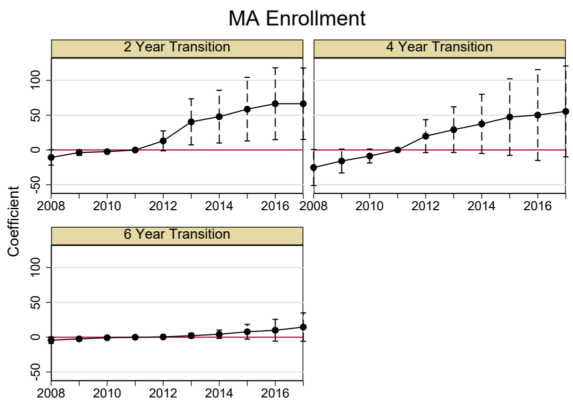
(c)



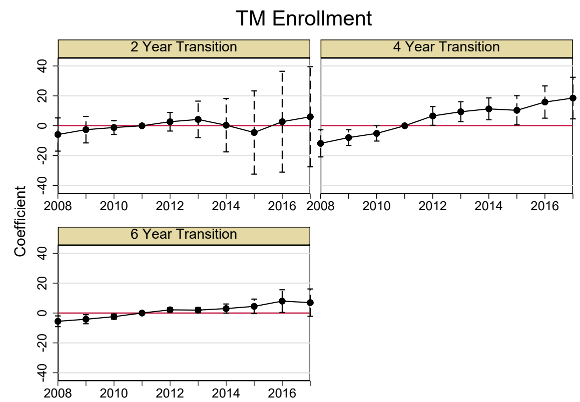
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on firm entry. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

Figure E.6: ACA benchmark event studies: average enrollment, 2008–2017

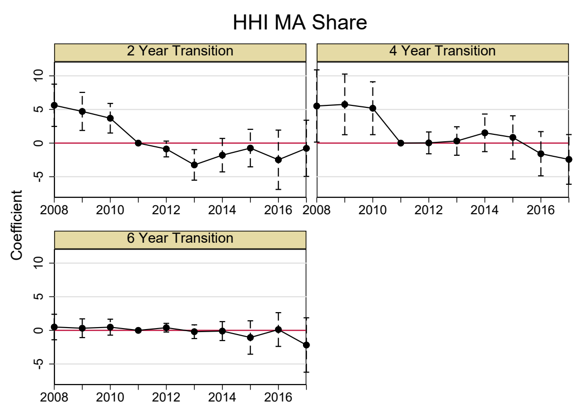
(a)



(b)



(c)



Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on firm entry. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

Table E.1: Summary of sample restrictions, 2017–2018

	Traditional Medicare		Medicare Advantage		Overall	
	N	Share	N	Share	N	Share
Individual criteria						
Initial sample	81,710,363	100	42,626,265	100	124,336,628	100
Age < 65	12,802,560	15.7	5,564,770	13.0	18,367,330	14.8
Months Part A $\neq$ months Part B	11,197,972	13.7	341,081	0.8	11,539,053	9.3
ESRD or disabled	917,720	1.1	565,679	1.3	1,483,399	1.2
Invalid county ID	139,523	0.2	6,921	0.0	146,444	0.1
Alaska, Guam, Puerto Rico, or Virgin Islands	240,568	0.3	909,508	2.1	1,150,076	0.9
Missing risk score input	296,473	0.4	13,578	0.0	310,051	0.3
MA criteria						
SNP, ESP, Part B only, or outside footprint			11,821,593	27.7	11,821,593	9.5
Missing plan characteristics			327	0.0	327	0.0
Non HMO or local PPO			3,000,316	7.0	3,000,316	2.4
Multiple segments			2,576,255	6.0	2,576,255	2.1
Analysis sample	56,115,547		17,826,237		73,941,784	
Unique beneficiaries					40,141,182	
Plan-year observations					3,702	
Unique plans					2,263	

Notes: This table summarizes the criteria used to isolate the analysis sample. These are based on individual and Medicare Advantage characteristics. Each row reports the number of beneficiaries impacted by each restrictions. The "N" column reports the number of beneficiaries and the "Share" column reports this value as a share of the initial sample of all Medicare beneficiaries.

Table E.2: Impact of ACA reform on county benchmarks, 2008–2017

	(1) Average Benchmark	(2) Average Benchmark	(3) NQB Benchmark	(4) NQB Benchmark	(5) QB Benchmark	(6) QB Benchmark
Post-ACA Transition	-43.10***	-58.46***	-58.06***	-71.44***	-32.01***	-47.50***
	(1.38)	(1.71)	(1.50)	(1.79)	(1.29)	(1.66)
Year FEs	✓	✓	✓	✓	✓	✓
County FEs	✓		✓		✓	
Mean of dependent variable	746.21	746.21	737.21	737.21	749.76	749.76
F	4,444.8	915.7	4,204.7	980.1	5,470.3	874.1
Observations	15,056	15,056	15,056	15,056	15,056	15,056

Notes: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors clustered at the county-level. This table reports estimates for the impact of the ACA on MA county benchmarks. An observation is a county-year. Monetary values are converted into 2008$. The sample contains counties in my analysis sample prior to 2012 and counties that completed their transition to the complete post-ACA benchmarks (counties had either 2, 4, or 6 years to transition). "NQB" stands for no quality bonus and "QB" stands for quality bonus. "Average Benchmark" measures the most ACA enrollment weighted average benchmark.

Table E.3: Summary statistics of MA sample, 2017–2018

	Other MA					Utilization sample				
	Mean	SD	P10	P90	N (1,000s)	Mean	SD	P10	P90	N (1,000s)
Demographics										
Age	74.9	7.3	67.0	86.0	11,517.0	75.0	7.3	67.0	86.0	6,309.3
Female (%)	56.6	49.6	0.0	100.0	6,515.8	56.4	49.6	0.0	100.0	3,558.5
Low income (%)	10.5	30.6	0.0	100.0	1,207.5	11.0	31.3	0.0	100.0	696.3
New Medicare (%)	3.9	19.3	0.0	0.0	447.5	3.8	19.0	0.0	0.0	236.7
New Medicaid (%)	0.4	6.6	0.0	0.0	49.6	0.4	6.2	0.0	0.0	24.4
Died (%)	3.1	17.3	0.0	0.0	357.2	3.1	17.4	0.0	0.0	198.1
Active choice (%)	21.0	40.8	0.0	100.0	2,432.5	22.9	42.0	0.0	100.0	1,443.3
Risk score (IP)	0.9	0.8	0.5	1.2	11,517.0	0.9	0.9	0.5	1.2	6,309.3
Risk score (IP-OP-CAR)	1.1	1.1	0.4	2.2	11,517.0	1.3	1.2	0.4	2.7	6,309.3
Util (Std. $)					11,517.0	8,415.2	24,230.9	0.0	21,848.4	6,309.3
Util (Std. $) | Use					11,517.0	9,716.8	25,793.5	0.0	24,721.3	6,309.3
Markets										
Average age	71.6	1.1	70.4	73.2	11,517.0	71.5	1.1	70.3	72.9	6,309.3
Female (%)	54.4	1.4	52.7	56.1	11,517.0	54.5	1.5	52.5	56.3	6,309.3
Rural (%)	14.7	20.8	0.4	45.7	11,208.4	15.3	21.2	0.2	47.4	6,089.7
College (%)	31.1	9.7	18.6	44.1	11,517.0	30.5	9.4	18.4	42.8	6,309.3
White (%)	77.6	15.7	55.8	95.2	11,517.0	78.7	15.0	55.8	95.0	6,309.3
Median income	23,787.7	5,669.5	17,686.5	31,964.9	11,517.0	23,103.9	5,163.6	17,381.9	30,145.4	6,472.7
Medicaid eligible (%)	20.8	8.4	12.0	33.6	11,517.0	19.9	8.2	11.4	31.3	6,309.3
Medicare death rate (%)	3.7	0.4	3.3	4.2	11,517.0	3.7	0.4	3.3	4.2	6,309.3
Sample size										
Beneficiary-years					11,517.0					6,309.3
Beneficiaries					6,491.8					3,613.5
Panel sample					0.0					4,000.4

Notes: This table compares Medicare Advantage beneficiaries in our analysis sample based on whether they were enrolled in a contract with a high degree of data completeness. All beneficiaries in one of these contracts enter the utilization sample and are used to estimate the health state parameters. "Active Choice" measures whether a beneficiary changed their coverage option relative to the prior year or if they were new to the Medicare program. Healthcare utilization is measured in terms of standardized dollars. All market demographics except the rural share, college degree, and median income are measured for the Medicare population.

Table E.4: Summary statistics of TM sample, 2017–2018

	Other TM					Utilization sample				
	Mean	SD	P10	P90	N (1,000s)	Mean	SD	P10	P90	N (1,000s)
Demographics										
Age	75.4	8.0	66.0	87.0	48,531.0	75.3	7.8	66.0	87.0	7,584.5
Female (%)	55.7	49.7	0.0	100.0	27,018.3	59.7	49.0	0.0	100.0	4,528.5
Low income (%)	12.4	33.0	0.0	100.0	6,015.7	17.7	38.1	0.0	100.0	1,340.3
New medicare (%)	5.0	21.7	0.0	0.0	2,414.3	4.1	19.8	0.0	0.0	310.9
New medicaid (%)	0.6	7.5	0.0	0.0	275.1	0.7	8.2	0.0	0.0	51.4
Died (%)	4.1	19.9	0.0	0.0	2,004.7	4.1	19.8	0.0	0.0	308.5
Active choice (%)	5.6	22.9	0.0	0.0	2,703.4	4.6	21.0	0.0	0.0	350.3
Risk score (IP)	1.0	1.1	0.5	1.6	48,531.0	1.1	1.2	0.5	1.8	7,584.5
Risk score (IP-OP-CAR)	1.0	1.1	0.4	1.7	48,531.0	1.7	1.6	0.4	3.5	7,584.5
Util (Std. $)					48,531.0	10,586.5	20,049.5	518.8	28,559.3	7,584.5
Util (Std. $) | Use					48,531.0	10,889.4	20,253.0	647.2	29,209.7	7,584.5
Markets										
Average age	71.4	1.2	69.9	72.9	48,531.0	71.4	1.2	69.9	73.0	7,584.5
Female (%)	54.2	1.7	52.1	56.0	48,531.0	54.2	1.7	52.1	56.1	7,584.5
Rural (%)	24.5	27.0	0.6	67.1	47,249.7	24.4	27.1	0.5	67.1	7,375.7
College (%)	29.6	11.1	15.8	45.0	48,531.0	29.9	11.2	15.8	45.7	7,584.5
White (%)	80.9	15.0	59.2	96.1	48,531.0	81.0	15.0	58.5	96.2	7,584.5
Median income	23,579.1	6,140.8	16,842.2	32,353.7	48,531.0	23,735.5	6,185.3	16,889.6	32,734.7	7,584.5
Medicaid eligible (%)	19.1	7.6	11.0	29.9	48,531.0	19.2	7.8	11.0	30.3	7,584.5
Medicare death rate (%)	3.7	0.4	3.3	4.3	48,531.0	3.7	0.4	3.3	4.3	7,584.5
Sample size										
Beneficiary-years					48,531.0					7,584.5
Beneficiaries					26,501.6					4,101.9
Panel sample					0.0					6,751.2

Notes: This table compares Traditional Medicare beneficiaries in our analysis sample based on whether they appear in the claims data. Beneficiaries with claims data enter the utilization sample and are used to estimate the health state parameters. “Active choice” measures whether a beneficiary changed their coverage option relative to the prior year or if they were new to the Medicare program. Healthcare utilization is measured in terms of standardized dollars. All market demographics except the rural share, college degree, and median income are measured for the Medicare population.

Table E.5: Parameter estimates

Variable		Parameter	SE
Health state distribution			
Mean μ_h	Risk score Q_1	0.280	0.002
	Risk score Q_2	0.578	0.002
	Risk score Q_3	0.683	0.002
	Risk score Q_4	1.144	0.002
	Female	-0.004	0.0001
	Low income	0.014	0.0003
	Age > 84	0.024	0.0003
	Market mortality rate	0.050	0.0003
	Market Medicaid eligibility	-0.024	0.0003
Variance σ_h			
	Risk score Q_1	0.856	0.001
	Risk score Q_2	0.787	0.001
	Risk score Q_3	0.767	0.001
	Risk score Q_4	0.662	0.001
Hassle cost ϕ			
	TM	-1.917	0.020
	MA HMO	0.478	0.003
	MA PPO	0.856	0.006
Mean moral hazard $\log \omega$	Constant	-1.375	0.003
Unobs het $\sigma_\mu, \sigma_\omega$	Health state mean	0.980	0.003
	Moral hazard	0.032	0.002
	Corr($\mu_h, \log \omega$)	-0.636	0.011
Demand			
Premium α	Mean	-12.586	0.259
	Low income	-3.548	0.125
Utilization utility β	Mean	11.571	0.255
	Low income	-0.150	0.010
TM-MA switching cost ι		-8.620	0.129
CARA ψ		-4.530	0.326
Contract FEs		✓	
Year FEs		✓	
Star rating FEs		✓	
Beneficiary-year observations		73,941,784	
Plan-year observations		3,702	

Notes: This table reports estimates for the health state distribution and demand parameters. Estimates are obtained from a two-stage GMM procedure that targets observed utilization and plan choice decisions and IV restrictions. Confidence intervals are constructed from standard errors obtained from the variance-covariance matrix of the GMM estimator.

Table E.6: Supplemental revenue as a function on plan characteristics, 2017–2018

	Supplemental revenue
High generosity plan	0.48***
	(0.01)
HMO	0.20***
	(0.01)
Year FE	✓
Plan star rating	✓
Mean of Dep Var	0.85
Observations	3,700

Notes: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Robust standard errors are in parentheses. This table reports estimates from an OLS regression of the supplemental revenue an MA plan needs to fund additional benefits relative to TM onto MA plan characteristics. Supplemental revenue is measured in thousands of dollars annually per-beneficiary. The unit of analysis is at the plan level.

Table E.7: Model predicted outcomes at observed market structures and shocks

	Baseline	Cut benchmarks $1,200
Endogenous firms		
Markets entered	11	11
Plans entered	3	3
Enrollment (1,000)	38.80	43.00
Enrollment share (%)	4.91	5.65
Markets entered by plan	10	10
Utilization ($1,000)	2.11	2.33
Profit ($1,000)	0.88	0.24
All products		
MA share (%)	10.20	5.53
MA utilization ($1,000)	2.53	2.31
TM utilization ($1,000)	5.19	5.07
Consumer surplus ($1,000)	0.21	0.08
Government MA spending ($1,000)	0.97	0.49
Government TM spending ($1,000)	4.66	4.79
Total government spending ($1,000)	5.63	5.29
Net welfare ($1,000)	-5.38	-5.19

Notes: This table reports the model predicted values at the observed market structures and unobserved demand and pricing shocks. This version of the model allows for selection to impact firm costs. The first column reports the model predictions for the observed outcome under no policy change. The second column simulates the impact of reducing Medicare Advantage plan benchmarks by $1,200 holding fixed market structures and shocks at observed values.

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