Entry and Competition in Insurance Markets: Evidence from Medicare Advantage*

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Abstract

Governments frequently turn to private markets to deliver public benefits. This structure can lower the government's costs if it designs a payment system that attracts competitive firms with cost controls the government lacks. In this paper, I analyze the implications of this system for the Medicare Advantage program. I use administrative data to develop and estimate a model of firm entry and product offering decisions that captures how firms endogenously respond to government policies as well as consumer sorting and utilization of health insurance. I then use the model to simulate other payment policies in Massachusetts. I find that under the current design, the government overpays firms for their participation and the enrollment they generate. Under a policy that lowers firm payments and transfers a portion of this money to consumers, the government can reduce spending by roughly $276 million ($350 per enrollee). This policy incentivizes similar firm participation and enrollment, while more equitably distributing surplus across healthy and sick consumers.

Keywords: competition, endogenous plan menus, entry, Medicare Advantage

JEL Codes: D82, G22, H75, I11, I13, L11, L13

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I Introduction

As of 2021, the U.S. government spends nearly $830 billion—10% of all spending—each year on healthcare for seniors in the Medicare program (Cubanski and Neuman, 2023). The majority of beneficiaries receive these benefits through Traditional Medicare (TM), the public insurance option. The remainder receive coverage through Medicare Advantage (MA), which are private insurance plans that are subsidized by the government. There are at least three policy rationales for subsidizing a private market for Medicare benefits. First, private firms have developed expertise in limiting moral hazard healthcare utilization, which allows these companies to deliver benefits at lower cost. Second, competition lower premiums and offer products with extra services not covered by TM (e.g., vision, dental, hearing, etc.) or financial coverage to attract enrollees. Third, competition also gives firms an additional incentive to lower their costs, which generates additional savings for the government. This structure for using private markets to deliver public goods appears in other settings, including education and housing (see e.g., Baum-Snow and Marion, 2009; Hoxby, 2000; Neilson, 2021; Poterba, 1996).

Promoting entry and robust participation in insurance markets faces several challenges. Chief among these are adverse selection—the tendency for sicker people to prefer more generous insurance plans—and moral hazard—the propensity to consume additional healthcare because it is cheaper—are the most salient. Concerns about selection may lead to firms offering plans with less generous coverage in markets with sicker patients or failing to enter these markets altogether—a behavior typically referred to as "cream skimming." Firms must also contend with the existence of the public option. Traditional Medicare offers baseline coverage—which has gaps and higher out-of-pocket costs—at a relatively low premium. The private market must be competitive on both of these dimensions—coverage and premium—to attract enrollment. These forces create challenges for the design of government policies (i.e., subsidies) to support the private market. The policy must not only incentivize participation, it also needs to address selection and consumer price sensitivities. This is a difficult problem to solve because evaluating counterfactual policies requires a model that captures the complex interplay between policy, firm entry, and product offering decisions, as well as consumer plan and healthcare utilization choices. Prior work has captured some of these features in isolation, but we lack a unified framework that incorporates each of these components.

In this paper, I develop a model of firm entry and product offering decisions in health insurance markets. The framework captures how firms endogenously modify their participation decisions in response to changes in policy, competitive conditions, and consumer demand. I estimate the model using administrative data from the Medicare program. Since the data includes the new Medicare Advantage encounter data, I am able to measure healthcare utilization in these private plans.[1] I then use the model to run counterfactual simulations to evaluate the impacts of policies to promote participation in the Medicare Advantage market. There are three key findings. First, subsidies are necessary to support the existence of this private health insurance market. If no subsidy is provided, firms are unable to effectively compete against the public option to attract enrollees. Second, under its current form Medicare Advantage is not full taking advantage of the private market's expertise since healthier individuals tend to enroll in the private market more than sicker ones. Third, current policies used in Medicare Advantage overpay for the outcomes they deliver. The overpayment is driven by a risk adjustment system that distorts costs to the government.[2] An alternative policy that resolves this distortion along with a subsidy targeted at low-income seniors—who tend to have greater health needs—can deliver comparable outcomes to current policies, while lowering government costs by \$276 million (approximately \$350 per enrollee) and distributing surplus more equitably across health and sick individuals.

Medicare Advantage is an attractive setting to study the supply side of insurance markets. Private insurers administer and operate insurance plans that receive a subsidy to

[1]To my knowledge, this is the first paper in economics to leverage these data resources.

[2]The risk adjustment formula used in Medicare Advantage aims to capture how costly an individual that enrolls in Medicare Advantage is relative to a typical Traditional Medicare beneficiary.

account for the health status of each beneficiary they enroll. Plans that report costs below benchmarks for the government's costs of providing TM also receive additional payments to fund extra services or better cost sharing benefits for their enrollees. In two descriptive analyses, I show how this subsidy policy creates variation in plan choice set generosity and how this variation separately identifies adverse selection and moral hazard. This feature enables me to design a rich model of the supply side of this insurance market that captures how healthcare utilization driven by adverse selection and moral hazard impacts firm decisions.

The model has two stages. In the first stage, firms choose which markets to enter and which insurance products to offer. These choices are made to optimize net profits, taking into account the actions of their rivals, subsidies from the government, expected consumer demand, the healthcare utilization of their enrollees, and the fixed costs of entry. Demand and healthcare utilization are then realized in the second stage of the model. Access to administrative data allows me to capture rich levels of observable and unobservable heterogeneity in the estimation of consumer preferences and healthcare utilization. These components of the model capture how consumer selection across plans not only responds to, but also influences, the entry and product offering decisions of firms in equilibrium. I estimate firm fixed costs using moment inequalities derived from revealed preference assumptions to rationalize observed entry and product offerings. As a result, my model can characterize equilibria resulting from different subsidy policies.

Model estimates indicate consumers are price sensitive and value their expected utility from healthcare consumption. Consistent with the incentives of private health plans to control costs, I find that MA plans have significant utilization costs to reduce the amount of healthcare their beneficiaries consume relative to TM. These utilization costs are also effective at limiting the amount of moral hazard utilization their enrollees consume. Individuals in this market display a modest amount of risk aversion, consistent with the high level of financial generosity of Medicare Advantage plans in terms of coinsurance rates and out-of-pocket maximums. My estimate for the identified set of firm fixed costs captures the costs of establishing a provider network, the efficiency of entering markets with existing networks, and per-plan regulatory costs. Finally, I perform a series of exercises that demonstrate how allowing for selection and endogenous participation impacts predictions from my model. My results illustrate how models without these features may overstate the effects of counterfactual policies on consumer welfare and government spending.

I then use the model to weigh the tradeoffs of promoting firm participation in Medicare Advantage markets. To preserve tractability, I simulate outcomes for a single state (Massachusetts) and restrict firm strategies to enter groups of counties and offer products at the network type-financial generosity level (i.e., HMO or PPO and low or high generosity). The current policy in this market is to subsidize firms for each beneficiary they enroll. I start by assessing whether the government needs to subsidize a private market for Medicare benefits. Absent subsidies, premium competition with the public option—Traditional Medicare—leads the private market to unravel. Medicare Advantage plans offer a more generous product relative to TM and absent a subsidy, these firms cannot profitably attract enrollment because of the premium competition with TM. In other words, subsidies are necessary to sustain the existence of the private market. While eliminating subsidies results in the lowest amount of government spending, it ignores many of the other benefits MA has for consumers in the form of insurance products that are more financially generous than TM.

Having established that subsidies are necessary to sustain the private market, I consider whether alternative systems can deliver better outcomes for the program. In particular, I focus on whether alternative systems can improve how consumers sort between TM and MA as well as deliver cost savings to the government. In the first scenario, I eliminate the supply subsidy and transfer the average observed firm subsidy to consumers. This policy expands the size of the private market by 73% on average as healthier beneficiaries leave TM—exacerbating the positive selection into Medicare Advantage. Mechanically, the demand subsidy allows plans with low costs to effectively have a negative premium, which is not permissible under the supply subsidy. Government spending increases by 14% (over

\$651 million) due to the expansion of the private market. Thus, subsidies play a significant role in terms of influencing who enrolls in Medicare Advantage. Absent a targeted policy that induces sicker people to enroll in Medicare Advantage before the healthier ones, the government is unlikely to realize any of the potential savings promised by the program.

In the second scenario, I simulate a targeted policy that addresses deficiencies in the observed policy and untargeted simulated policy. The target policy has three components: a reduction in supply side subsidy benchmarks, a means tested demand subsidy, and an improved risk adjustment formula for supply subsidies. This targeted approach delivers market outcomes—firm entry and enrollment—similar to the observed policy. Government spending under this policy falls by over \$276 million on average, which is approximately \$350 per enrollee. Finally, this measures improves the distribution of consumer surplus across beneficiary health statuses. This exercise shows that there is room to improve how this private insurance market is regulated and may be able to deliver on its promised cost savings.

This paper contributes to our understanding of promoting choice in health insurance markets by rigorously capturing the role of the supply side of the market. Prior work in this space has weighed the value of offering choice based on an analysis of consumer demand. Prominent examples are Marone and Sabety (2022) and Ho and Lee (2022). Both extend the framework of Einav et al. (2013), which allows consumers to adjust their health spending based on their insurance coverage (i.e., moral hazard) to understand when consumer choice over insurance products with different levels of coverage is desirable. Both find there are limited gains to offering choice over different levels of financial coverage if a sufficient baseline level is offered.[3] My contribution extends these analyses by adding demand model of comparable richness to a complete model of health plan supply—one that not only captures decisions about entry but also product variety. These features allow my framework to

[3]Ho and Lee (2022) note that the gains from choice can improve if choice over financial and non-financial characteristics are offered. Wagner (2022) explores the conditions under which it is optimal to offer plan menus with plans differentiated in terms of their financial coverage and network types.

determine what entry and product offering decisions will arise endogenously under different policy regimes, taking account of the demand response. As a result, I can expand our understanding of the tradeoffs associated with incentivizing firm participation in competitive insurance markets.

My analysis also extends prior work on endogenous participation in insurance markets. Kong et al. (2022) and Geddes (2022) study how policies to mitigate adverse selection can induce greater insurer entry into markets and allow enhanced competition to improve consumer welfare. Miller et al. (2021) focus on how firms endogenously alter their plan characteristics in response to subsidization policies, while holding participation fixed. My model builds on this work by capturing both margins—firm participation and plan offering decisions are endogenous within my framework. These features are necessary to fully quantify how counterfactual policies may alter firm decisions and their impacts on consumers. For example, while a model that allows firms to endogenously reposition their product offerings to changes in policy, they rule out equilibria where it is optimal for the firm to exit the market altogether. This action may carry different implications for consumer welfare than the change in product characteristics induced by the policy. A contribution of my analysis is to simulate a model that captures both of these margins for supply to respond.

My work also contributes to the literature studying the equilibrium effects of adverse selection and the design of health insurance markets. Examples include Einav et al. (2019), which develops a framework to weigh the tradeoffs between demand subsidies and risk adjustment in a joint framework. Tebaldi (2022) assesses the ability of targeted subsidies to alter selection patterns to improve market outcomes for consumers, and Polyakova and Ryan (2020) document how imperfect competition can distort the efficiency of targeted demand subsidies. Closely related to my analysis, Curto et al. (2021) studies the current regulatory framework used in MA—sometimes referred to as "managed competition"—as a model for insurance markets.[4] I extend these analyses by studying how managed competition in MA

[4]There is an extensive literature on Medicare Advantage in economics that has some bearing on my paper.

impacts firm participation and product offering decisions. As a result, my model can answer whether managed competition generates sufficient entry or product offerings that are valuable to consumers and whether alternative regulatory schemes perform better at achieving these outcomes.

Finally, this paper relates to prior studies of product repositioning and firm entry. A common challenge for papers in these literatures is handling multiple equilibria. While Berry (1992) opted to model an outcome common to all equilibria, recent work has looked to partial identification methods to estimate the set of parameters consistent with multiple model equilibria (e.g., Ciliberto and Tamer, 2009; Eizenberg, 2014; Fan and Yang, 2020, 2022; Wollmann, 2018; and Ciliberto et al., 2021). My own analysis relies on partial identification based on moment inequalities generated by revealed preference to account for multiple equilibria in the spirit of Pakes et al. (2015). Methodologically, I combine models of entry and product repositioning by capturing how firms choose to offer different types of products in different geographic markets. Moreover, my findings highlight the importance of accounting for endogenous participation when performing counterfactual analyses that alter firm entry incentives.

The paper proceeds as follows. In Section II, I present the empirical setting with a description of the Medicare Advantage program and the data I use in my analysis. The model is presented in Section III. In Section IV, I present my identification strategy and a descriptive analysis that tests its validity. I then discuss estimation in Section V followed by results and model fit in Section VI. In Section VII, I simulate how alternative policies impact firm entry and product offering decisions as well as their associated welfare benefits and costs. Section VIII concludes.

Examples include how insurers invest and compete over non-premium characteristics captured by quality measures (Vatter, 2022); overpayments associated with the risk adjustment system (Geruso and Layton, 2020); whether risk adjustment has attenuated the incidence of risk selection between MA and TM (Brown et al., 2014 and Newhouse et al., 2015); the pass-through of plan subsidies to consumers (Cabral et al., 2018 and Duggan et al., 2016); and the impact of plan quality on mortality (Abaluck et al., 2021).

II Empirical Setting

This section provides an overview of Medicare Advantage's institutional background and the data I use in my analysis. Each year, beneficiaries eligible for Medicare must choose between Traditional Medicare and Medicare Advantage to receive healthcare coverage. Traditional Medicare, composed of Medicare Part A and Part B, covers inpatient and outpatient services (e.g., hospital visits, doctor appointments, lab tests, etc.). Since Traditional Medicare is provided by the government, most healthcare providers accept it as payment under a fee-for-service system. Medicare Advantage (originally called Medicare Part C) are health insurance plans administered by private firms and subsidized by the government. The plans are required to cover the same services as Traditional Medicare at a minimum, but typically include additional services not covered by Traditional Medicare like vision, dental, and prescription drugs.[5] Since Medicare Advantage is private insurance, enrollees must navigate a network of acceptable providers. Traditional Medicare do not have to navigate these restrictions. While both Traditional Medicare and Medicare Advantage have out-of-pocket (OOP) costs for enrollees (e.g., premiums, deductibles, copays, etc.), they tend to be lower for Medicare Advantage plans.[6] Appendix Figure E.1 provides a more detailed breakdown of the Medicare program and the coverage options available to seniors.

II.A Medicare Advantage

Medicare Advantage dates back to the early 1980s. The goal of the program was to use private firms to deliver Medicare services to tap into two potential benefits. The first benefit stems from the expertise of private firms. Health insurance companies have developed strategies and mechanisms that can reduce the amount of healthcare enrollees consume as well as increase the services offered to consumers. The government is unable to accomplish these

[5]Traditional Medicare enrollees may supplement their coverage with a Medicare Part D plan, which covers the costs of prescription drugs.

[6]Traditional Medicare enrollees may purchase Medigap policies to cover some of these costs.

goals under Traditional Medicare in its current form and could realize significant cost savings by relying on these private firms to deliver Medicare benefits. The second benefit relates to competitive markets. Competition creates incentives for these firms to further lower their costs, which generates additional savings for the government. These forces also lower premiums, which allow consumers to more readily access products with additional services.

The initial design of the program was unable to deliver these benefits. The primary issue stemmed from selective firm participation. Historically, the Centers for Medicare and Medicaid Services (CMS) set payment rates for MA plans. Insurers tended to participate in years when CMS offered higher payments or in specific geographies where the payments were greater or had healthier patients ("cream-skimming"). These behaviors hampered the ability of the Medicare Advantage to deliver its potential benefits to the government. These circumstances motivated a series of reforms to the program that created the regulatory structure currently in place.

To address concerns about firm participation, Congress authorized a new system for determining subsidies paid to Medicare Advantage plans.[7] The system is organized around benchmarks that reflect the government's costs of providing TM benefits to a typical beneficiary. CMS sets these rates annually at the county-level and they are observed by insurers. CMS considers each county a distinct market and limits enrollees to choose among plans offered in their county of residence. Insurers submit estimates for their costs of providing Medicare coverage to that population for each plan they offer.[8] Let b_j and B_j denote the requested subsidy and government cost benchmark for plan j, respectively. The government will pay plan j $\min\{b_j, B_j\}$ for each individual the plan enrolls. If $b_j < B_j$, the plan also receives a "rebate" payment the plan must use to fund additional benefits. Alternately if $b_j > B_j$, then the difference between the subsidy and the benchmark is passed along to con-

[7] While CMS uses the term "bidding system" and "bid" when discussing this process, they do not resemble auctions and I avoid using these terms when possible to prevent confusion.

[8] Insurers generally submit a single bid for each offered plan. Insurers are allowed to breakup a plan's footprint into multiple segments and submit separate bids for each segment. In practice the use of multiple segments is rare and I abstract from them in this paper.

sumers as part of the plan's premium. Medicare Advantage plans can also charge premiums if they offer additional benefits relative to TM.

Risk adjustments were also introduced by Congress to address concerns about Medicare Advantage targeting healthier populations. The purpose of risk adjustment is to scale the subsidies paid to plans based on the health of each enrolled beneficiary. These transfers to plans are adjusted linearly based on a beneficiary's risk score which is calculated by CMS (i.e., the subsidy for a beneficiary with a risk score 1.1 is 10% larger). Given this adjustment structure, enrollment in MA plans is typically weighted by beneficiary risk scores. The base risk score is the output of a CMS model that takes beneficiary demographics (i.e., age, gender, Medicare eligibility, and Medicaid status) and specific types of diagnoses from the prior year.[9] The base scores are then normalized by a factor based on TM costs such that the typical TM beneficiary has a risk score equal to one. Finally, risk scores for MA beneficiaries are scaled down to account for more intense coding of diagnoses for MA beneficiaries.[10]

II.B Data

My analysis uses information from 2016–2018 and primarily relies on three types of administrative data from the Medicare program. First, for every beneficiary eligible for Medicare, I observe their demographic information and choice of MA plan or TM. The second are medical claims for beneficiaries that enroll in TM. For a 20% random sample of TM beneficiaries each year, I observe their inpatient, outpatient, and physician claims. I also have access to inpatient discharge records for 100% of the Medicare population. The third are records of encounters between MA beneficiaries and medical providers, which CMS recently made available for research. These files contain information similar to medical claims except for

[9] The diagnoses that are included in the risk score calculation come from inpatient and outpatient hospital stays, physicians, and clinically trained non-physicians (e.g., psychologist, podiatrist, etc.). New beneficiaries that do not have recorded diagnoses from the prior year use a different CMS model to calculate their base risk score.

[10] This pattern is referred to as "upcoding" and is pervasive among MA plans. This behavior costs the government more than $650 per-enrollee each year and is too large to be offset by the current adjustments used by CMS (Geruso and Layton, 2020).

service payments. The MA encounter data cover 100% of inpatient and outpatient records and physician encounters for a cohort of over 12 million beneficiaries, which covers roughly 52% of MA beneficiaries in my analysis sample. These data allow me to construct choice probabilities, risk scores, and county-level demographics for the Medicare population.

I supplement the administrative data with four additional sources. The first are characteristics for every MA plan offered including the plan's premium, network type, and financial generosity as measured by expected out-of-pocket costs. The second are worksheets that firms complete to receive their subsidies from the government. In particular, these files contain the specific subsidy amount the firm requested for the plan, how the plan's premium is broken down between the base and supplemental premium, how much supplemental revenue is required to fund extra benefits, and the allocation of rebate payments to cover these benefits. This paper appears among the first in economics to leverage both the MA encounter data alongside plan-level subsidies, which are both essential for my analysis of Medicare Advantage. Third, from DRG InterStudy I observe whether a firm offers other insurance products (i.e., commercial group, commercial individual, Medicaid managed care, etc.) at the county-level. Finally, I obtain information on provider supply and market characteristics from the Health Resources Services Administration, American Hospital Association, and Census Bureau. Appendix A provides a detailed summary of every data set and its use within this paper.

I restrict my analysis to beneficiaries eligible for Medicare due to age (i.e., non-disabled and non-ESRD) and are enrolled in TM or a MA HMO or Local PPO plan.[11] I also exclude employer sponsored, special needs plans, and Part B only plans. I drop a small number of individuals because they are missing information necessary to calculate risk scores or are enrolled in a MA plan with missing characteristic information. See Appendix A and Appendix Table E.1 for a detailed discussion of the sample criteria. After using the 2016 data

[11] "ESRD" refers to end-stage renal disease. Citizens in the United States diagnosed with ESRD are eligible for Medicare benefits regardless of their age. HMO stands for Health maintenance organization and PPO stands for Preferred provider organization.

to construct risk scores, my full sample for 2017–2018 contains 73,941,784 beneficiary-year observations and 40,141,182 unique beneficiaries. The utilization sample contains 4,424,824 beneficiary-years (2,410,546 beneficiaries). The full sample contains 3,702 plan-year observations for 2,263 unique MA plans.

Table 1 contains summary statistics for the Medicare Advantage markets in my sample. Beneficiaries typically face a premium of \$20 a month for MA plans, nearly all of which is used to fund supplemental benefits. MA plans are heavily subsidized by the government—the typical subsidy and rebate payments are approximately \$750 and \$66 per-beneficiary-per-month, respectively—consistent with the benchmarks CMS sets for each market. CMS estimates that the average MA beneficiary will have \$140 per-month (\$1,680 annually) in out-of-pocket costs. The average market has seven plans offered by three firms. The majority of these plans are HMOs, which tend to have lower costs, narrower networks, and cost controls relative to Local PPOs. Roughly three of the plans in the menu are considered "high generosity" based on monthly out-of-pocket cost estimates. Despite having several plans, most plan menus are highly concentrated, which suggests plans may have considerable power in these markets.

III Empirical Model

III.A Overview

This section provides an overview of the model. It begins with a description of individuals and their role within the model, followed by a similar treatment for firms and the government. The summary concludes with a discussion of timing and equilibrium.

Individuals. The model captures the decision of a senior eligible for Medicare, denoted by i, about their health insurance coverage for year t. These individuals are characterized by groupings of observed demographic characteristics (i.e., combinations of age, gender, low-income status, pre-existing health diagnostics, etc.) that are indexed by c, risk aversion ψ, and a propensity to consume additional healthcare when its price falls ω. These characteristics are the private information of individuals and not observed by firms, which may create a selection problem from the health insurer's perspective.

Individuals face a series of choices in the model. First, the senior must decide whether to enroll in a Medicare Advantage plan or Traditional Medicare. At the time of this choice, they do not know the realization of their health state for the year h_{it}. As a result, individuals form expectations about their health state and healthcare consumption. This expected healthcare utilization along with risk aversion and preferences for other plan characteristics factor into an individual's health insurance coverage choice.

After choosing a health plan, individuals realize their health state and must now decide how much healthcare to consume. An individual chooses the optimal amount of healthcare to consume Q^*_{ijt} by weighing the benefits of utilizing healthcare and their associated costs. These costs include administrative measures firms implement to limit healthcare consumption ϕ_{ijt} and the out-of-pocket costs paid by an individual given their chosen plan's cost structure $OOP_{jt}(Q^*_{ijt})$. More financially generous health plans have lower out-of-pocket costs, which may induce some individuals to consume extra healthcare—sometimes referred to as "moral hazard."

Firms. The model also captures the decisions of firms that may participate in Medicare Advantage markets. The set of potential entrants are firms that are endowed with CMS contracts to offer Medicare Advantage plans within a specified service area A—typically a state. These firms possess expertise and employ practices that allows them to offer health insurance benefits more efficiently, which is among the reasons why the government wants to tap into this private market to deliver these benefits. The model captures these efficiencies with the utilization cost parameter ϕ_{ijt} that appears when individuals choose how much healthcare to consume.

In the model, firms decide what counties within a service area to enter and which products to offer. In this setting, products are health insurance plans—indexed by j—which have two key dimensions. The network type (i.e., HMO or Local PPO) is the first dimension. The type of network influences the form and strength of the utilization costs plans can use to control the amount of healthcare their enrollees consume. HMO plans are generally more restrictive than PPO plans. The second dimension is whether the plan has a high or low level of financial generosity. This decision impacts the amount of out-of-pocket costs enrollees pay for consuming healthcare. Both of these characteristics impact the amount of healthcare individuals expect to consume, which enters their health plan decision. After making these choices, firms set premiums for their plans based on the subsidies they request from the government.

Firm participation decisions are made on the basis of net profits, which are the difference between variable profits and fixed costs. Firms form expectations of what their variable profits will be given their own market entry and product offering decisions as well as those of their rivals. Variable profits will depend on who enrolls in each plan and how much healthcare those individuals consume. Fixed costs are a function the products and markets the firm chooses to enter. These fixed costs represent the costs associated with provider networks, regulatory compliance, and market research. The optimal participation decision for a firm maximizes net profits given the participation decisions of rival firms.

Government. The model captures the government's role in setting policies that impact the functioning of this market. The first is Traditional Medicare's cost sharing, which determines the amount TM beneficiaries pay out-of-pocket for their healthcare consumption. The second is the subsidy scheme to pay to Medicare Advantage plans. Under the current system the government sets county level cost benchmarks B_{mt} each year that reflects the historic costs the government has paid to provide TM benefits to individuals in county m. Firms observe these benchmarks and submit subsidy requests that reflect their costs for providing TM benefits to this population b_{jt}. These requests are evaluated against cost benchmarks to determine whether the plan receives a rebate payment to fund additional benefits or if any costs are passed along to consumers as part of the plan's premium p_{jt}.

Equilibrium. This model captures the strategic interaction between firms—indexed by n—that decide to enter Medicare Advantage markets. The model is set up as a two stage game and is summarized in Figure 1. During Stage 1, firms observe their fixed costs and the distribution of shocks they will face in Stage 2. Given this information and the cost benchmarks B_{mt}, firms simultaneously decide which plans to offer in each market within a service area. In Stage 2, firms choose their subsidies which determines the premiums for their plans. A firm's strategy is a bundle of $(\mathcal{J}_{nA}, \mathbf{b}_{nt})$, where $\mathcal{J}_{nA}$ is the set of plans (i.e., network type and generosity level) the firm chooses in Stage 1 to offer in each market within service area A and $\mathbf{b}_{nt}$ is the vector of subsidies the firm chooses in Stage 2 for each plan.

The model has a subgame perfect equilibrium (SPE).[12] For a given set of Stage 1 strategies $\mathcal{J}_A$, the firm subsidy choices $\mathbf{b}_t$ constitute a Nash equilibrium. When choosing these strategies, firms internalize how consumers will sort across plans offered to them and how they will consume healthcare given those plan choices. Formally, firms make their participation and subsidy decisions for service area A to maximize net profits:

$$\max_{(\mathcal{J}_{nA}, \mathbf{b}_{nt})} \Pi_{nA}(\mathcal{J}_{nA}, \mathcal{J}_{-nA}, \mathbf{b}_{nt}, \mathbf{b}_{-nt}) - F_{nA}(\mathcal{J}_{nA}) \tag{1}$$

where Π and F are firm n's variable profits and fixed costs respectively and $-n$ denotes the strategies of firm n's rivals. A strategy $(\mathcal{J}^*_{nA}, \mathbf{b}^*_{nt})$ is a SPE if it maximizes firm n's net profits given the strategies played by rivals $(\mathcal{J}^*_{-nA}, \mathbf{b}^*_{-nt})$

The model may have multiple equilibria. This multiplicity arises from different real-

[12] I assume the existence of the subgame perfect equilibrium for this model. Proving the existence of the equilibrium is beyond the scope of this paper.

izations of unobservable fixed costs for firms that can alter the set of markets the firm enters or products that are offered in those markets. Thus multiple SPE are possible where firms may optimally choose different $\mathcal{J}_A^*$'s that result in a unique Nash equilibrium for the subsidy choices $\mathbf{b}_t^*$. The following sections present the details of the model and its components. Consistent with solving for SPEs these components are presented in reverse order.

III.B Demand

III.B.1 Healthcare utilization

This component of the model captures how an individual chooses how much healthcare to consume given their health insurance plan and realization of their health state h_{it}. The optimal amount of healthcare for an individual to utilize Q_{ijt}^* maximizes their utility given its associated costs, which depend on the type of plan the individual chose.[13] Formally, an individual chooses Q_{ijt}^* to solve:

$$\max_{Q_{ijt}} \quad u(Q_{ijt}; h_{it}, \omega_i, j) = v(Q_{ijt}, h_{it}, \omega_i) - \phi_{ijt} 1[Q_{ijt} > 0] - OOP_{jt}(Q_{ijt}) \tag{2}$$

where

$$v(Q_{ijt}, h_{it}, \omega_i) = Q_{ijt} - h_{it} - \frac{1}{2\omega_i h_{it}}(Q_{ijt} - h_{it})^2 \tag{3}$$

$$\phi_{ijt} = \exp(\mathbf{X}_{ijt}^{\phi} \boldsymbol{\beta}^{\phi}) \tag{4}$$

Following Einav et al. (2013) the value of healthcare utilization in Equation (3) is quadratic in the difference between the individual's healthcare utilization and health state. Intuitively, an individual aims to align their healthcare consumption with the need implied by their health state. The parameter ω_i captures how responsive an individual's healthcare

[13]Healthcare utilization is composed of inpatient, outpatient, physician, and hospice services. I do not model choices for prescription drug coverage and do not include it in my measure healthcare utilization.

utilization decision is to its costs and is typically interpreted as the individual's elasticity of demand for healthcare or moral hazard. Like Ho and Lee (2022), the moral hazard parameter is interacted with an individual's health state, which implies that the effect of moral hazard is increasing in an individual's health need. Individuals face two costs associated with healthcare utilization. The first is a "utilization cost" captured by ϕ_{ijt}, which was first introduced by Ho and Lee (2022). This term captures the barriers individuals navigate to access care. As show in Equation (4), cost varies with the network type of the plan an individual has chosen (i.e., TM, MA-HMO, or MA-PPO).[14] The second cost of utilization is the out-of-pocket costs, which are represented by $OOP_{ijt}(\cdot)$ and varies by plan type (i.e., network type and generosity level). Details about these cost structures and the solution to the utilization problem are available in Appendix B.

III.B.2 Health state distribution

The health state of individuals follows a log normal distribution $F_{it}(h)$:

$$\log h_{it} \sim \mathcal{N}(\mu_{it}, \sigma^2_{h,it}) \tag{5}$$

As noted in the literature, this distribution assumption captures the right skew in healthcare utilization. Variation in the parameters μ_{it} and $\sigma_{h,it}$ generates selection based on health need in the model by altering the amount of healthcare an individual chooses to consume. This selection is allowed to arise from both observable and unobservable characteristics.

The mean of an individual's health μ_{it} and moral hazard ω_i are jointly normally distributed as follows:

$$\begin{bmatrix} \mu_{it} \\ \log \omega_i \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mathbf{X}^{\mu}_{it}\boldsymbol{\beta}^{\mu} \\ \mathbf{X}^{\omega}_{i}\boldsymbol{\beta}^{\omega} \end{bmatrix}, \begin{bmatrix} \sigma^2_{\mu} & \\ \sigma_{\mu,\omega} & \sigma^2_{\omega} \end{bmatrix} \right) \tag{6}$$

where the means are a function of observable characteristics $\mathbf{X}^{\mu}_{it}$ for the health state mean

[14] Utilization costs may also depend on individual characteristics. The current version of the model limits utilization costs to depend on network type. I plan to relax this modeling choice in a future version.

and a constant for the moral hazard mean $\mathbf{X}_i^\omega$. Unobserved heterogeneity in μ_{it} and $\log \omega_i$ arise through the joint distribution's variance and covariance parameters. The variance of the health state distribution $\sigma_{h,it}$ is modeled as a projection onto observable characteristics $\mathbf{X}_{it}^\sigma$:

$$\sigma_{h,it} = \mathbf{X}_{it}^\sigma \boldsymbol{\beta}^\sigma \tag{7}$$

At the time of their plan choices, individuals know the parameters of their health state distribution μ_{it} and $\sigma_{h,it}$ as well as moral hazard ω_i. This information influences their plan choice, which is how selection on both health and moral hazard arises within the model. Let θ_1 summarize the parameters of the health state distribution and utilization costs to estimate. This vector includes the mean shifters $\{\boldsymbol{\beta}^\mu, \boldsymbol{\beta}^\omega, \boldsymbol{\beta}^\sigma, \boldsymbol{\beta}^\phi\}$ and the variance-covariance parameters $\{\sigma_\mu, \sigma_\omega, \sigma_{\mu,\omega}\}$.

III.B.3 Plan choice

Individuals must choose among the health insurance plans in their market's plan menu $\mathcal{J}_{mt}$. Markets are defined as a county-year pair, where counties are indexed by m. An individual chooses the health insurance plan $j \in \mathcal{J}_{mt}$ that maximizes their expected utility over their health state distribution.

$$\max_{j \in \mathcal{J}_{mt}} \quad U_{ijmt} = \int -\exp(-\psi \times l_{ijmt}(h)) dF_{imt}(h) \tag{8}$$

where

$$l_{ijmt} = \delta_{jmt} + \alpha_{it} p_{jt}(b_{jt}) + \beta_{it} u(Q_{ijt}; h_{it}, \omega_i, j) + \iota_{ijmt} + \epsilon_{ijmt} \tag{9}$$

$$\delta_{jmt} = \theta_2 X_{jmt} + \xi_{jmt} \qquad \alpha_{it} = \alpha_0 + \alpha_1 y_{it} \qquad \beta_{it} = \beta_0 + \beta_1 y_{it}$$

The coefficient of absolute risk aversion is denoted as ψ and is common to all beneficiaries. To rule out risk-loving preferences, I constrain the CARA coefficient to be non-negative $\psi = \exp(\beta_\psi)$. The term l_{ijmt} summarizes the utility individual i receives from plan j. The outside option is Traditional Medicare ($j = 0$) whose expected utility is normalized to one.

The factors that enter l_{ijmt} are noted in Equation (9). The first term is the mean utility of the plan common to all individuals in the market. This mean utility may depend on observable characteristics like the plan's star rating or provider network (X_{jmt}) and an unobservable demand shock ξ_{jmt}. The second term is the plan premium $p_{jt}(b_{jt})$, which may differentially impact beneficiaries with low-incomes (y_{it}).[15] The third component is the individual's utility they will receive from the plan given their health state realization and the amount of healthcare they expect to utilize. These quantities depend on the amount of out-of-pocket costs and the utilization costs the individual will incur, which depend on the network type and generosity of plan j. The fourth component ι_{ijmt} captures the switching costs of changing from TM to MA. The switching cost is only incurred for beneficiaries changing out of TM from the prior year and not beneficiaries that pick a coverage option for the first time. This term captures inertia in plan choices and the strength of TM as the default enrollment option. The final component is the idiosyncratic logit taste shock ϵ_{ijmt}.

As noted previously, individuals are classified into categories based on their observable characteristics, which are indexed by c. Let s_{cjmt} denote the probability that individuals in group c in market mt choose plan j.[16] The plan's market share s_{jmt} is obtained by integrating these choice probabilities over the distribution of observable types within the market. Finally, let θ_3 denote the parameters in the utility function that are independent of mean utility $\{\beta_\psi, \alpha_0, \alpha_1, \beta_0, \beta_1, \iota\}$.

[15] I do not observe a continuous measure for income in my data. The administrative data contain indicators for low-income status.

[16] Individual of the same type have the same amount of expected healthcare utilization.

III.C Supply

III.C.1 Subsidy choice and plan premiums

Continuing backwards, the next action within the model is how plans choose their subsidy payments from the government. A firm chooses the subsidy for each plan by maximizing their expected profits across all markets the plan entered within a service area.[17] Let A_{jt} denote the set of counties plan j entered within service area A in year t. Given the set of plan offering decisions the firm made in Stage 1 $\mathcal{J}_{nAt}$, the firm chooses the subsidy vector $\mathbf{b}_{nt}$ by solving:

$$\max_{\mathbf{b}_{nt}} \quad \Pi_{nAt} = \int \sum_{j \in \mathcal{J}_{nAt}} \sum_{m \in A_{jt}} \sum_{c \in C} \left[\mathrm{MR}_{cjmt} - \mathrm{MC}_{cjmt}\right] s_{cjmt}(\mathbf{b}; \theta) M_{cmt} dF_{ct}(h) \tag{10}$$

where M_{cmt} is the number of type c beneficiaries in market mt and MR_{cjmt} and MC_{cjmt} are specified as:

$$\mathrm{MR}_{cjmt} = \bar{r}_{cmt} \min\{b_{jt}, B_{jt}\} + p_{jt}(b_{jt}) \qquad \mathrm{MC}_{cjmt} = \Lambda_{jt} Q^*_{cjt}(h) + \lambda_{jt} \tag{11}$$

The marginal revenue for enrolling an individual of observed type c is denoted by MR_{cjmt}. Two items contribute to marginal revenue. The first is the subsidy payment the plan receives from the government, which is equal to the requested b_{jt} if the request is below the plan's cost benchmark $B_{jt} = \sum_{m \in A_{jt}} B_{mt} w_{mt}$, where w_{mt} are market size weights.[18] If the requested subsidy is above the benchmark, the plan's subsidy payment is equal to the benchmark. These payments from the government are risk adjusted based on the average risk score of beneficiaries of observed type c in the market $\bar{r}_{cmt}$. The second and third components of marginal revenue are the plan premium, which depends on the subsidy request for the

[17] In general service areas are states. A more detailed discussion of service areas is provided in Appendix B.

[18] In practice county-level benchmarks are weighted by the plan's projected enrollment. Market size weights ease the burdens for computing the model's solution. Market size is also strongly correlated with realized enrollment.

plan. Premiums are discussed later in this section.

The marginal cost for a type c individual denoted by MC_{cjmt}. This cost is broken down into components. The first term captures how plan costs depend on the amount of healthcare they expect beneficiaries will consume. The term Λ_{jt} represents the price that MA plan j pays providers for the healthcare utilization of the beneficiaries in their plan. Prior empirical work has documented that MA plans tend to pay similar prices to healthcare providers as TM.[19] Consistent with these fact patterns I assume $\Lambda_{jt} = 1$. The second term λ_{jt} is an unobserved cost that captures non-utilization contributions to marginal costs.

The policy environment makes Medicare Advantage plan premiums a function of the plan's subsidy b_{jt} and whether the plan offers additional benefits relative to TM. These features are clear when looking at the two components of the plan premium paid by consumers:

$$p_{jt}(b_{jt}) = \underbrace{\max\{b_{jt} - B_{jt}, 0\}}_{\text{base}} + \underbrace{\max\{\mathrm{SR}_{jt} - \mathrm{Rebate}_{jt}, 0\}}_{\text{supplemental}} + \varepsilon_{1jt} \tag{12}$$

where $\mathrm{Rebate}_{jt} = \max\{\kappa_{jt}(B_{jt} - b_{jt}), 0\}$ and the size of κ_{jt} depends on the star rating of the plan.[20]

The supplemental revenue MA plans need to provide additional benefits is denoted as SR_{jt}. Plans can offset these costs if they receive a rebate payment. The term ε_{1jt} is an unobservable measurement error that rationalizes Equation (12) at observed subsidies. I model the amount of supplemental revenue a plan needs to fund additional benefits relative to TM as function of plan characteristics W_{jt} that includes the plan's network type, quality rating, and generosity level. The variable ε_{2jt} denotes an efficiency shock the plan receives to the amount of revenue required to fund these extra benefits.

$$\mathrm{SR}_{jt} = \theta_4 W_{jt} + \varepsilon_{2jt} \tag{13}$$

[19] See e.g., Curto et al. (2019), Pelech (2020), and Trish et al. (2017).

[20] The levels of κ_{jt} are 0.50 if the plans has 3 stars or fewer, 0.65 if the plan has 3.5 or 4 stars, and 0.70 if the plan has 4.5 or 5 stars.

III.C.2 Fixed costs of entry

Firms are endowed with CMS contracts that define the set of possible plans they may offer within a service area A. Each year, firms decide which plans they will offer in each market within the service area. The primary fixed cost of entry into a market is establishing a new or updating an existing network of providers enrollees may use to receive healthcare services. A Medicare Advantage plan's provider network must annually certify that it meets network adequacy and access criteria established by CMS. Given this institutional setting, it is useful to think of the entry decision as reoccurring each year, which abstracts from distinctions between sunk vs fixed costs of entry.

I assume that a firm's fixed cost for offering MA plans is additively separable across markets and has an observable and unobservable component. For expositional ease, I drop the year subscript t. Let A_n denote the set of markets that firm n has chosen to enter within service area A. The fixed cost for insurer n to offer MA plans in service area A is:

$$F_{nA} = \sum_{m \in A_n} [F_{nm} + \nu_{2nm}] \tag{14}$$

The observable component of the fixed cost of entering market m has three parts. The first measures the number of plans the firm has chosen to enter into market m. The second and third components are measures of provider supply. Specifically, H_m measures the number of hospital systems in the market and P_m denotes the number of primary care physicians active in the market. These terms are intended to capture—in a reduced form manner—the costs of bargaining with providers to join the firm's network. I allow the parameters on these terms to vary based on whether firm n has an existing provider network in the market from another insurance segment (e.g., commercial group, individual, exchange etc.). This feature captures efficiencies some insurers may have that eases entry into Medicare Advantage.

$$F_{nm} = \rho_1[\text{Number of plans}]_{nm} + \rho_{2n} H_m + \rho_{3n} P_m \tag{15}$$

where

$$\rho_{\{2,3\}n} = \rho_{\{2,3\}\text{net}} 1[\text{Other presence}]_{nm} + \rho_{\{2,3\}\text{none}} \left(1 - 1[\text{Other presence}]_{nm}\right) \tag{16}$$

The unobserved component of fixed costs are denoted by ν_{2nm}, which are independent over time. These costs are observed by firms when making their Stage 1 decisions and the selection problem they create is discussed more in Section V.

After observing ν_{2nm}, firms simultaneously choose which plans to enter into a market by weighing their expected profits against their fixed costs of entry. Firms calculate their expected profits over the joint distribution of the Stage 2 unobservables $e = (\xi, \varepsilon_1, \varepsilon_2)$. I assume that firms know the form of this distribution but not the realizations they will face. Finally, ν_{1A} denotes a mean zero expectation error, which implies firms on average accurately predict their variable profits across all markets within a service area. Thus a firm will add plan j to the set of products it offers in the service area $\mathcal{J}_{nA}$ if the expected profits of offering the plan exceed its fixed costs:

$$\underbrace{\sum_{j \in \mathcal{J}_{nA}} \mathop{\mathbb{E}}_{e} \left[\Pi_{jA}(A_n; e)\right] + \nu_{1jA}}_{\text{expected variable profits}} - \underbrace{\sum_{m \in A_n} \left[F_{nm} + \nu_{2nm}\right]}_{\text{fixed costs}} \geq 0 \tag{17}$$

IV Identification

This section describes how the model is identified and presents an analysis that illustrates the validity of the identification strategy. I demonstrate how CMS policies act as a plausibly exogenous source of variation to the financial generosity of the health insurance choice sets faced by consumers. The variation in insurance plan generosity induced by these policies is essential to separately identify the parameters governing healthcare utilization and consumer preferences in the model.

IV.A Strategy

The objects to identify in the model are the joint distribution of individual health states, moral hazard, utilization costs, and consumer preferences for differentiated health insurance plans. The ideal data set for this exercise has two key characteristics. First, it would track individuals over time and measure their health states. Second, the data would contain variation in how individuals are exposed to different choice sets of health insurance plans with alternate levels of financial coverage. The source of this variation in plan choice sets is driven by exogenous changes in a policy instrument. This data set would capture how plan enrollment and healthcare utilization changes as variation in the policy alters the average level of financial generosity the health plan choice set. This data set could facilitate non-parametric identification of the model's parameters.

In most practical applications the ideal data set is not obtainable and additional assumptions are required. Relative to the ideal data set, my administrative data has substantial cross-sectional variation in health insurance plan choice sets—every county in the United States—but relatively short panel variation—two years after constructing ex ante risk scores. Given these realities, parametric assumptions are necessary to assist identification. The benchmarks CMS sets at the market-level each year are a source of variation in the generosity of health insurance plans in consumer choice sets. These market-level benchmarks form the plan-level benchmarks firms face when making their product offering decisions. Thus, variation in the benchmarks in other markets provides a plausibly exogenous source of variation in the generosity of the plans in a market's choice set.

Given these parametric assumptions and plausible exogenous variation in choice sets, the parameters associated with healthcare utilization are identified. The extent to which consumers make similar healthcare utilization choices when facing similar choice sets over time identifies the persistent component of the health state distribution. Variation in healthcare utilization over time among similar individuals, aided by the distributional assumption, identifies unobserved heterogeneity in these decisions. The parameters that influence moral hazard—the propensity to consume more healthcare when it is less expensive—are identified by variation in healthcare utilization as the generosity of choice sets respond to variation in CMS benchmarks. Deviations from trends in healthcare utilization by network type induced by variation in benchmarks identifies changes in the threshold health need for healthcare consumption (i.e., utilization costs).

These sources of variation also identify consumer preferences for health insurance plans. Risk aversion is identified by how consumers choose health plans as variation in benchmarks alters the generosity of plans within consumer choice sets. The extent to which consumers with comparable health needs pick more generous plans captures a measure of their tolerance for uncertainty about the out-of-pocket costs associated with their expected health need. Preferences for plan characteristics that are common across its footprint are identified by the extent to which consumers opt into the plan across markets and over time. Switching costs from TM to MA are identified by the extent to which TM beneficiaries retain this coverage over time.

To address the potential correlation between unobserved plan-market level demand shocks and the premiums chosen by firms, I rely on instrumental variables. These instruments must be correlated with a plan's premium but independent of the plan-market shock. Many instruments are possible in this setting including variations of the widely used Berry et al. (1995) and Hausman (1997) instruments. I use two types of instruments. The first set are based on CMS policies which are exogenous to firm pricing decisions yet correlated with a plan's subsidy choice and premium. Specifically, I use functions of the CMS benchmarks across a plan's footprint and a plan's marginal revenue around the benchmark—determined by the κ parameter. The second set of instruments are demographics from non-overlapping markets of rival plans. The intuition for the market demographics instruments follows Fan (2013). Healthcare utilization is correlated with observable characteristics. Thus, the demographics of the Medicare population in a county influence the costs of offering a MA plan.

Suppose there are two plans A and B, which overlap in market 1, while only plan B is present in market 2. The demographics of market 2 directly impact plan B's choices and indirectly impact plan A's choices through the competition channel in market 1. Thus, the demographics from market 2 can serve as an instrument for plan A's choices in its markets.

Finally, the fixed costs of entry within the model are partially identified. These parameters cannot be point identified without imposing additional assumptions about which of the model's multiple equilibria arises. I use a revealed preference approach in the spirit of Pakes et al. (2015) to derive moment inequalities that are consistent with these multiple equilibria. Revealed preference is based on the assumption that firms are making optimal decisions based on the information available to them at the time of their action. This condition allows me to determine that other choices the firm could have made—yet did not—must be weakly less profitable. In Section V, I illustrate how I use this assumption to derive unbiased moment inequalities to recover the identified set of fixed cost parameters. I further leverage an exclusion restriction based on the independence of the unobservables in the firm's entry problem over time to provide additional bounds on the identified set.

IV.B Testing Identification Strategy

This section uses reduced form methods to highlight variation in my setting that is critical for the identification of my model of health insurance supply and demand. First, I demonstrate how government policies influence the characteristics of MA plans in local markets. These policies act as a plausibly exogenous source of variation that induces plans to offer different levels of financial generosity. As a result, variation in these policies creates variation in the average generosity of the plan choice sets consumers face. I then demonstrate how this variation in plan choice set generosity allows me to separately identify healthcare utilization driven by private health information from moral hazard—an essential feature to identify the model of healthcare utilization and demand.

How policy influences plan entry and characteristics. I demonstrate how firms respond to changes in their payments following the implementation of the Affordable Care Act (ACA). As discussed in Section II, firms offering Medicare Advantage plans receive two payments from the government. The first is a subsidy for every beneficiary they enroll and the second is a rebate that is paid to plans that request subsidies below the government's TM cost benchmarks. Rebates must be used to provide more generous benefits to enrollees.

In an effort to control costs, the ACA took steps to reduce payments to Medicare Advantage plans. This law transitioned county cost benchmarks to a new system that more closely aligned with Traditional Medicare costs.[21] Plans face a weighted average of the county-specific benchmarks where they entered when choosing their subsidies. This structure allows consumer sorting and healthcare utilization from other geographies to influence the products that are available in local markets. Thus variation in these county-level benchmarks across markets can act as a source of plausibly exogenous variation in plan subsidy and rebate payments, which affects entry incentives and the characteristics of the insurance products consumers face.

To test whether this is a valid source of policy variation, I empirically assess whether cross-market variation in CMS benchmarks predicts the generosity of insurance plans in a market. For each plan j in county m in year t, I construct the plan's leave-one-out benchmark $B_{jt\setminus m}$ as:

$$B_{jt\setminus m} = \sum_{k \in A_{jt}\setminus m} w_{jkt} B_{mt} \tag{18}$$

where A_{jt} denotes the set of counties where plan j entered in year t and w_{jkt} are weights based on the number of people plan j enrolled in market k such that $\sum_{k \in A_{jt}\setminus m} w_{jkt} = 1$. The notation $A_{jt} \setminus m$ denotes the set of counties plan j entered in year t, excluding market m.

After constructing the leave-one-out benchmarks for each plan, I aggregate benchmarks,

[21] A detailed discussion of the ACA reforms is available in Appendix C.

entrants, and plan characteristics—weighting by plan enrollment—to the market level. Then I run regressions of the following form:

$$Y_{mt} = \beta_0 + \beta_1 B_{t\setminus m} + \beta_m + \beta_t + \epsilon_{mt} \tag{19}$$

where Y_{mt} is the market-level outcome (i.e., total entrants or average plan characteristic), $B_{t\setminus m}$ is the market average leave-one-out benchmark for the plans active in market m in year t, and β_m and β_t are county and year fixed effects respectively. The sample for these regressions are counties with Medicare Advantage plans in 2016–2018. This time period includes the first year when all counties completed their transition to the ACA payment system. Results are robust to the inclusion of earlier years.

Table 2 reports the estimated effects of cross-market benchmark variation on firm participation and the financial generosity of Medicare Advantage plans in a market. Participation is measured by the number of firms and plans in a county. My estimates indicate that the leave-one-out benchmark does not predict the number of firms active in a market, but does have a positive and significant relationship with the number of plans in the market. In other words, higher benchmarks are associated with more plan entry. One way to interpret this pattern is that benchmarks can influence the intensive participation margin but firms are likely to enter these markets even when benchmarks are low. This interpretation is arguably consistent with the fact that most firms offering MA plans are active in other insurance segments and have already paid the sunk costs of entry.

I considered four measures of the financial generosity of Medicare Advantage plans: CMS estimates of the dollar value of extra coverage in MA plans relative to TM, rebate payments used to fund additional benefits, supplemental premiums which plans only charge if they provide additional benefits relative to TM, and the supplemental revenue plans need to fund additional benefits relative to TM. Each of these outcomes are directly observable in CMS data. For each outcome the estimated coefficient on the leave-one-out benchmark is significant and has the correct sign. Higher average benchmarks predict MA plans have more extra coverage relative to TM, larger rebate payments, and require more supplemental revenue to fund benefits relative to TM. Each of these measure are consistent with more generous insurance offerings. Higher average benchmarks also predict lower supplemental premiums with marginal statistical significance. This pattern is consistent with plans earning higher rebates, which can offset the costs plans would otherwise charge consumers for offering these additional benefits.

Taken together, this analysis highlights how variation in CMS benchmarks can induce plausibly exogenous variation in firm participation and the generosity of the health insurance choice sets consumers face in their local market. As the cost benchmarks change each year, firms update their plan offerings, subsidy requests, and collect rebate payments. These rebates are reinvested by the plans to provide additional benefits relative to TM. In Appendix C, I provide further evidence of how firms respond to changes in benchmarks with event studies documenting their responses to the ACA reforms.

Decomposing healthcare utilization. The previous section illustrated how government policy creates plausibly exogenous variation in the generosity of the health insurance plans available to consumers across markets. This section demonstrates how this variation in plan menu generosity can be used to decompose healthcare utilization driven by private health information and moral hazard. Quantifying and decomposing these patterns is important for motivating the structure of the equilibrium model of health plan demand that can account for selection on health information as well as moral hazard. These two components are necessary to fully capture the policy environment where firms leverage their expertise to control these costs when offering more generous insurance products relative to the public option.

To get a sense for the incidence of selection in Medicare, Figure 2 plots average healthcare utilization along two margins. The left panel compares utilization among TM and

MA beneficiaries unconditionally and conditional on the six most common groupings of observable characteristics.[22] TM beneficiaries tend to utilize more healthcare than MA beneficiaries unconditionally and conditional on observable characteristics. This pattern could be explained by either unobserved health differences (selection) or steps MA plans take to manage the amount of healthcare their enrollees consume (impacting moral hazard). The right panel compares utilization among MA beneficiaries across plans with different levels of financial generosity. Utilization tends to be greater in MA plans with a high level of financial generosity unconditionally and conditional on observed characteristics. Greater health needs or moral hazard could rationalize the higher utilization in more financially generous MA plans.

Variation in plan menu generosity created by MA benchmarks is essential for separating moral hazard utilization from health driven utilization. The validity of this design requires that the generosity of plan menus is exogenous to unobserved factors that may impact the amount of healthcare an individual consumes. If this assumption holds, then the extent to which observably similar beneficiaries facing health plan choice sets with differing levels of financial generosity use different amounts of healthcare can be attributed to moral hazard as opposed to private health information. The prior section documented how plausibly exogenous variation in benchmarks across markets can induce variation in plan choice set generosity. Firms observe these new benchmarks each year and subsequently make their participation and plan offering decisions. I tests whether plan choice set generosity induced by this plausibly exogenous policy variation isolates moral hazard healthcare utilization by estimating the following model at the individual level:

$$Q_{ijt} = \beta_0 + \beta_1 \text{Choice Set Gen}_{m_{(i)}t} + \beta_2 \mathbf{X}_{it} + \beta_3 \mathbf{K}_{m_{(i)}t} + \beta_4 \mathbf{C}_{j_{(i)}t} + \beta_t + \epsilon_{it} \tag{20}$$

where Q_{ijt} measures the healthcare utilization of beneficiary i in plan j during year t;

[22] These groupings summarize a beneficiary's risk score, age, gender, income, and their county's Medicare mortality and Medicaid eligibility rates.

Choice Set $\text{Gen}_{m_{(i)}t}$ measures the financial generosity of the plan menu in market m; $\mathbf{X}_{it}$, $\mathbf{K}_{it}$, and $\mathbf{C}_{it}$ are vectors of individual, market, and plan controls respectively; and β_t is a time fixed effect.

Estimates for this model are presented in Table 3. The table presents two different measures of plan menu generosity. The first is the average rebate CMS paid to MA plans in a beneficiary's market, which firms are required to use to increase the financial generosity of their plans. Thus larger rebates should be associated with plans that provide coverage for more services or better cost sharing—characteristics of more generous plan menus—and higher levels of healthcare utilization. The second generosity measure is the probability that a beneficiary enrolls in a plan with a high level of financial generosity (as measured by OOPC).[23] As the probability of enrolling in a generous MA plan increases, we would expect to see a positive relationship between this menu generosity measure and healthcare utilization to be consistent with a moral hazard interpretation.

My estimates support the hypothesis that plan menu variation can separately identify healthcare utilization driven by moral hazard from private health information. Absent controls MA plan rebate payments have a positive and statistically significant correlation with healthcare utilization. This finding is robust to the inclusion of controls for the observed characteristics of a beneficiary, their market, and chosen MA plan. While there is no significant unconditional correlation between healthcare utilization and the probability of enrolling in a generous MA plan, once controls for observable characteristics are included, the relationship is positive and statistically significant. I leverage this variation in plan menu generosity to identify moral hazard within my model of health insurance demand and utilization.

[23]This probability is based on the observed market shares of MA plans in each market.

V Estimation

This section describes how the model is estimated. I follow the generalized method of moments to estimate the health state, consumer preference, and fixed cost parameters. The first subsection focuses on the Stage 2 parameters—health states and consumer preferences—and relevant implementation details. The second subsection describes how I derive the moment inequalities to recover the identified set of fixed cost parameters in Stage 1. This discussion includes a description of how the moment inequalities are used for inference.

V.A Health state and consumer preferences

Moments. To estimate the health state distribution parameters, I match moments based on healthcare utilization patterns. Specifically, I target the unconditional mean and variance of healthcare utilization as well as the mean and variance of utilization conditional on observables such as risk score quantiles. These moments help the model replicate the relationship between observable characteristics and healthcare utilization observed in the MA encounter and TM claims data. To capture the propensity to consume healthcare as its cost decreases (moral hazard), I include the mean and variance of the utilization distribution across quantiles of plan choice set generosity and risk scores. As discussed in the prior section, variation in healthcare utilization across choice sets with different levels of financial generosity captures utilization not driven by health need. Choice set generosity is measured by the average rebate payment all MA plans in the market received. To further capture "moral hazard" spending, I also target the average healthcare utilization conditional on being in the coinsurance region. I match the utilization cost parameters with the average probability of consuming no health care conditional on plan type.

I also include moments based on plan choices to estimate consumer preferences for health plans. To capture risk aversion and consumer sorting across plans, I target the average model choice probability to match the observed choice probability by observable consumer types. As discussed in Appendix B, I constrain plan-level market shares implied by the model to match their observed analogs. I also use moments based on IV restrictions in the demand model. This condition requires that the unobserved demand shock ξ_{jmt} is uncorrelated with a vector of instruments Z_{jmt}. In the prior section, I describe the types of instruments I use and the intuition they bring to the identification argument. The specific instruments that I use include the minimum, maximum, and mean benchmark over a plan's footprint; the plan's marginal revenue around the benchmarks; the number of hospitals, hospital beds, and primary care physicians active in a plan's footprint in the previous year; and the average characteristics of non-overlap rival counties (i.e., share rural, share with college degree, median income, share female, share white, share of all Medicare beneficiaries that died, and the share of Medicare beneficiaries eligible for Medicaid).

Implementation details. My analysis relies on the MA encounter data to measure healthcare utilization among MA beneficiaries. There are two challenges to working with these data. The first is the absence of payment information. I overcome this shortcoming by using a measure of healthcare utilization based on TM prices that was proposed by Jung et al. (2022) specifically for MA encounter data. I follow their implementation for deriving these standardized prices using all of the claims and encounter data available to me. I then merge these utilization metrics onto the MA encounter and TM claims data for consistency.

The second challenge relates to the completeness of the encounter data that private insurers report to CMS.[24] To attenuate this concern, I follow the procedures in Jung et al. (2022) to assess the completeness of the encounter data, which is based on comparing the encounter data to other sources that contain information about MA healthcare utilization (i.e., the Medicare Provider Analysis and Review (MedPAR) and the Healthcare Effectiveness Data Information System (HEDIS)). MA contracts have a high level of data completeness if they meet minimum thresholds for enrollment and the difference between

[24] "Completeness" is the notation that all encounter records for a plan's beneficiary appear in the data provided by CMS.

the number of hospitalizations, ambulatory, or emergency department visits recorded in the encounter data and MedPAR or HEDIS. Appendix Table E.3 highlights that there are no systematic differences between MA beneficiaries enrolled in plans with a high degree of data completeness relative to those that are not.[25] Additionally, the utilization patterns I observe across TM and MA beneficiaries are consistent with other studies that do not rely on encounter data, which further mitigates concerns about encounter data completeness (Curto et al., 2019).[26]

Risk scores play an important role in my analysis. The risk scores that CMS calculates for each Medicare beneficiary are generally not produced in the files made available to researchers. However, CMS does provide the algorithms to generate these risk scores based on the demographic and diagnosis information that is made available. I lack the data to fully replicate the CMS risk scores because I do not have utilization data for all Medicare beneficiaries. I address this challenge by approximating the CMS risk score using their published formula and the available to me diagnoses from inpatient claims and discharges, which I have for the universe of Medicare beneficiaries.[27] I first produce the base risk score using the CMS algorithm for the appropriate year with beneficiary demographics and prior year inpatient diagnoses. These base scores are then normalized by the average base score for all TM beneficiaries that year. Finally, risk scores for beneficiaries that were in a MA plan the previous year are deflated by the coding pattern adjustment reported by CMS.[28]

To assess the quality of my approximated risk score, I aggregate my scores to levels where CMS reports average risk scores. Figure 3 plots the distribution of average risk scores

[25] A similar exercise is presented in Appendix Table E.4 for TM beneficiaries. Individuals in the TM claims data are marginally more likely to be female or low income but the size of the difference is modest.

[26] Curto et al. (2019) find in 2010 for three MA insurers covering 40% of MA enrollees that the unadjusted difference in utilization in MA was 30% lower than TM. Since they also found that MA plans paid prices similar to TM, this gap can be directly attributed to reduced utilization of healthcare services by MA beneficiaries. Once controls are added this gap becomes 9–25% lower than TM. Due to the large growth in MA penetration since 2010, it is intuitive that this gap has gotten smaller over time as more TM beneficiaries enroll into MA plans.

[27] Since I have 100% of TM inpatient discharges, I have all diagnoses recorded in the inpatient claims that I do posses.

[28] These adjustments were 5.66% and 5.91% in 2017 and 2018, respectively.

at the county-level from 2017–2018 that I calculated against the values CMS reported for those counties. The means of the two distributions are nearly identical. The variance of the approximated risk score distribution is smaller relative to the true variance, consistent with the missing diagnoses. For a model of endogenous plan participation, approximating the risk score distribution well on average captures the first-order effects that impact whether a firm chooses to operate in a market. Any bias in the estimates of a firm's entry incentives from the reduced variance of the distribution is likely small.[29]

V.B Moment inequality derivation and inference

Derivation. To derive the moment inequalities I need the distribution of Stage 2 shocks and resolve the selection bias introduced by the unobserved fixed costs ν_{2nm}. The Stage 2 distribution of unobservables $e = (\xi, \varepsilon_1, \varepsilon_2)$ is required to calculate a plan's expected variable profits. I recover this empirical distribution given estimates for the Stage 2 model parameters $\Theta = \{\theta_1, \theta_2, \theta_3, \theta_4\}$. The unobserved fixed costs ν_{2nm} create a selection problem because firms observe these costs when making their entry decisions. This feature will introduce bias to the estimates for the identified set if unaddressed. I make two assumptions that allow me to address this bias.

Assumption 1. *Unobservable fixed costs ν_{2nm} are additively separable across plan-market specific unobservable fixed costs:*

$$\nu_{2nm} = \sum_{j \in \mathcal{J}_{nm}} \nu_{2njm} \tag{21}$$

Assumption 2. *Plan offered in adjacent markets within a service area—typically a state—has the same unobserved fixed cost ν_2.*

Assumption 2 is supportable when viewing the unobserved fixed costs as regulatory

[29] Appendix Figure E.2 plots the risk score distributions at the MA plan level using only inpatient diagnoses and all of the diagnoses necessary to compute risk scores.

compliance, business intelligence, and marketing, which are unlikely to vary meaningfully across markets. Firms likely rely on common personnel for these tasks and the amount of resources devoted to them likely scales with the number of markets a particular plan enters.

Unbiased moment inequalities are derived based on revealed preference and Assumptions 1 and 2. Revealed preference requires that the entry and product offering decisions observed in data are optimal relative to the other choices that the firm *could* have made. Let A_n and $\mathcal{J}_{nA}$ denote the observed market and product offerings decisions firm n made in service area A and A'_n and $\mathcal{J}'_{nA}$ denote their unobserved analogs. Revealed preference implies:

$$\sum_{j\in\mathcal{J}_{nA}} \mathbb{E}_e[\Pi_{jA}(A_n;e,\Theta)]+\nu_{1jA}-\sum_{m\in A_n}[F_{nm}+\nu_{2nm}] \geq \sum_{j\in\mathcal{J}'_{nA}} \mathbb{E}_e[\Pi_{jA}(A'_n;e,\Theta)]+\nu_{1jA}-\sum_{m\in A'_n}[F_{nm}+\nu_{2nm}] \tag{22}$$

Suppose the firm removes plan j from market m such that $A'_n = A_n \setminus m$. I rearrange the terms in Equation (22) such that:

$$\Delta \sum_{j\in\mathcal{J}_{nA}} \mathbb{E}[\Pi_{jA}(A_n, A'_n)] + \Delta\nu_{1jA}(A_n, A'_n) - F_{nm} - \nu_{2njm} \geq 0 \tag{23}$$

where $\Delta X(A_n, A'_n) = X(A_n) - X(A'_n)$.

I can derive a similar inequality by adding market m' to plan j's observed footprint such that $\hat{A}_n = A_n + m'$. Rearranging terms yields:

$$\Delta \sum_{j\in\mathcal{J}_{nA}} \mathbb{E}[\Pi_{jA}(A_n, \hat{A}_n)] + \Delta\nu_{1jA}(A_n, \hat{A}_n) + F_{njm'} + \nu_{2nm'} \geq 0 \tag{24}$$

The assumption that ν_{2nm} is separable across plans isolates a specific plan's ν_{2njm} shock for each perturbed market in Equations (23) and (24). Notice the assumption $\nu_{2njm} = \nu_{2njm'}$

if m and m' are adjacent allows me to bound ν_{2njm} and combine these equations such that:

$$\Delta^+ \sum_{\mathcal{J}_A} \mathbb{E}[\Pi(m,m')] + \Delta^+ \nu_1(m,m') - \Delta^- F(m,m') - \underbrace{(\nu_{2njm} - \nu_{2njm'})}_{\approx 0} \geq 0 \tag{25}$$

where $\Delta^+ X(m,m') = \Delta X(A_n, A_n') + \Delta X(A_n, \hat{A}_n)$ and $\Delta^- X(m,m') = \Delta X(A_n, A_n') - \Delta X(A_n, \hat{A}_n)$.

It remains to address the approximation errors ν_1. Recall that these errors are mean zero across all markets within a service area. This error is eliminated by averaging over all the pairwise combinations of Equation (25) for each market within a service area. This procedure yields a set of unbiased moment inequalities for plan j.

$$\mathbb{E}[m_j(\theta)] = \mathbb{E}[\Delta^- F(m,m') - \Delta^+ \sum_{\mathcal{J}_A} \mathbb{E}\,\Pi(m,m') - \Delta^+ \nu_1(m,m')] \leq 0 \tag{26}$$

where the expectation is taken over adjacent market combinations within a service area.

I generate additional inequalities by interacting each plan inequality with a set of "instruments" that are independent of the unobservable ν terms. Specifically, I leverage the independence over time assumption and use lagged counts of markets with existing provider networks and provider supply counts as instruments. These instruments are valid because the unobservable fixed costs are independent over time. These two types of moment inequalities form the null hypothesis for the inference procedure I use to construct an estimate for the identified set of fixed cost parameters.

Inference. I use these inequalities to conduct inference on the identified set of fixed cost parameters. I follow the inference procedure proposed by Chernozhukov et al. (2019), which is well-suited for models with many moment inequalities. Their procedures are built around a studentized test statistic that detects violations of the moment inequalities.

$$T = \max_{1 \leq k \leq K} \frac{\sqrt{D}\varphi_k}{\varsigma_k} \tag{27}$$

where k indexes the moment inequalities, K denotes the total number of inequalities, φ and ς are the mean and standard deviation of the moment inequalities, and D is the total number adjacent market pairs for a plans.

I implement the self-normalized one step procedure, which has a closed form for its critical values. This feature lowers the procedure's computational burden relative to multi-step or bootstrap alternatives. The tradeoff is that the identified sets may be more conservative. Additional details related to the computation of the moment inequalities and the inference procedure are presented in Appendix B.

VI Results

The top panel of Table 4 contains the demand parameter estimates. Parameter estimates for the health state distribution are available in Appendix Table E.5.[30] In general, parameter estimates have the correct sign and are significant. Demand slopes down in premiums with lower income beneficiaries having a higher degree of sensitivity. Consumer preferences also depend on the value of healthcare they expect to consume net of utilization and out-of-pocket costs. Enrollment choices respond more to upfront costs represented by premiums than expected costs or benefits under a particular plan. Estimated switching costs out of TM are large and consumer risk aversion is more consistent with risk neutral behavior.[31] More risk neutral behavior in this setting could reflect the low financial risk seniors face in this

[30]Estimates for the supplemental revenue regression are available in Appendix Table E.6.

[31]Switching costs between TM to MA range from \$530–680. The estimated CARA coefficient implies an individual would be indifferent between earning nothing and a 50-50 gamble where they win \$100 or lose \$99.89. The literature has produced similar estimates for the average level of risk aversion: Dickstein et al. (2023) \$99.32 and \$97.40; Ho and Lee (2022) \$99.97; Marone and Sabety (2022) \$91.70; Handel (2013) \$91; and Einav et al. (2013) \$84.

market. MA plans provide generous cost sharing and out-of-pocket maxima, which makes choosing among them akin to short term gambles over relatively small amounts of money.

The bottom panel of Table 4 presents quantities implied by the demand and utilization model. I start by evaluating the amount of moral hazard estimated by the model. In this context, moral hazard captures the propensity for individuals to consume more healthcare as the cost utilization falls. To measure this force, I simulate how healthcare utilization changes as the coinsurance rate moves from 100% to 0% holding deductibles and out-of-pocket maximums fixed. The changes in utilization are greatest for beneficiaries enrolled in TM (14.69%) relative to individuals in a MA plan (5.31%–6.97%).[32] The different magnitude of the moral hazard effects between TM and MA is consistent with utilization costs. MA plans take measures to limit the amount of healthcare their enrollees utilize, which are not present in TM. These effects are driven by the utilization cost parameters, whose implied dollar values are about $150 for TM, $1,230 for MA PPOs, and $1,610 for MA HMOs. These implied MA utilization costs are in line with estimates from Ho and Lee (2022) which ranged from $550–$1,710.

Table 5 contains estimates for the identified set of fixed cost parameters. For computational reasons, I use a subset of moment inequalities from 20% of service areas. The identified set does not contain zero for any of the fixed cost parameters and their signs have intuitive interpretations. For example, fixed costs increase with the number of plans offered within a market. This estimate appears consistent with the significant amount of regulatory compliance Medicare Advantage plans must satisfy and complete before entering the marketplace. My estimates suggest that fixed costs are substantially lower (roughly 75% based on the median of the intervals) in markets where the firm has an existing provider network. This finding is consistent with firms having to devote fewer resources to establish a provider network for their Medicare Advantage offerings.

[32] Other studies have estimated similar amounts of moral hazard: Dickstein et al. (2023) 22% and 11%; Ho and Lee (2022) 26.3% and 3.5%; Marone and Sabety (2022) 24% and 14%; and Einav et al. (2013) 30%.

VI.A Model Fit

Figure 4 presents a subset of the data moments targeted in estimation alongside their model predicted counterparts. The top panel contains the unconditional mean and variance of the utilization distribution, which the model almost perfectly matches. The middle panel shows the mean and variance of the utilization distribution conditional on risk score, which is a strong predictor of utilization. The model closely fits these moments as well with a modest under-fit of the mean and variance for the first two risk score quartiles. The bottom panel presents the fit for the probability of not utilizing healthcare by plan type. The model under-fits the moments for high-generosity plans and over-fits the low-generosity plans. However, this pattern is consistent with the model having a common utilization cost parameter for each network type.

Figure 5 presents non-targeted data moments alongside their model analogs. Overall, my model successfully captures how consumers sort across health insurance plans and utilize healthcare. The left panel shows average utilization by plan type and the right panel shows the variance of utilization by plan type. The model slightly over-predicts utilization in MA plans and under-predicts TM utilization. The model does replicate relative differences in observed utilization by plan types. For example, utilization is higher in TM than MA—consistent with utilization costs—and utilization is higher in more generous MA plans—consistent with more generous cost sharing. Capturing these patterns is important as they allow the model to reflect the selection patterns observed in Medicare and the supply side considerations firms face when deciding which markets to enter and types of products to offer.

Overall, the model fit is reasonable. On average the model closely matches observed utilization patterns by demographic characteristics. It slightly over-predicts the mean and variance of utilization in MA plans while under-predicting these quantities for TM. That said, the model accurately reflects sorting and utilization dynamics by plan types, which are key features for the supply side of the model.

VII Counterfactuals

In this section I use my estimated model to quantify the tradeoffs of promoting private firms to participate in the market for Medicare benefits. I describe the simulation setting and details in Section VII.A. To build intuition for later results, in Section VII.B I demonstrate how my modeling assumptions impact equilibrium outcomes. Then in Section VII.C, I simulate the effects of four distinct subsidy policies for promoting entry and participation in this competitive insurance market and quantify their tradeoffs.

VII.A Simulation setup

My simulations focus on the 2018 Massachusetts service area, which is summarized in Table 6. Like most MA markets, Massachusetts is highly concentrated. The top two firms—Blue Cross Blue Shield of Massachusetts (BCBS) and Tufts Health Plan (Tufts)—controlled over 56% of all MA enrollment in 2018. Tufts is the market leader and offers HMO plans of high and low generosity in 8 markets. BCBS primarily offers PPO plans of high and low generosity in 11 markets. The remaining share of the market is spread across five firms which primarily offer HMO plans.[33]

For the simulations, I make two assumptions for tractability. These assumptions can be relaxed as computational resources allow and do not alter the underlying model. First, I assume that BCBS and Tufts are strategic players that choose which markets to enter and which products to offer. Each firm is restricted to offering plan types that align with their observed network offering (i.e., HMO or PPO) but can choose the level of financial generosity of the plans they offer. The other firms are treated as a competitive fringe whose choices are taken as exogenous. Thus, the choice set for an endogenous firm is to offer no plan, a

[33]One of the these firms offers PPO and HMO plans but has a state-wide market share of 1%.

low generosity plan, a high generosity plan, or both. Second, I assume that entry decisions are made at the Combined Statistical Area (CSA) level. CSAs are groupings of counties used by the U.S. government for adjacent communities that demonstrate economic or social linkages.[34] Massachusetts has two CSAs; based around Boston and Springfield. I group all other counties in Massachusetts into a third pseudo-CSA. This assumption is supported by observed entry patterns in Massachusetts. Firms that enter one of the markets within a CSA typically enter the others as well. Thus, an endogenous firm must decide for each plan they offer whether to enter no markets, Boston-area markets, Springfield-area markets, other markets, or a combination of these markets. Given the number of players in the game, the size of their choice sets, and draws necessary to calculate expected profits, I need to compute 40,960 pricing equilibria for each counterfactual.

To solve for the equilibria of the model, I follow the procedure proposed by Lee and Pakes (2009). This method has been used by other papers that solve models with multiple equilibria (see e.g., Wollmann, 2018). The procedure uses a best response iteration approach to find the entry and product offering equilibria that are consistent with Stage 1 necessary conditions in Equation (17). I compute fixed costs similar to other moment inequality papers in the literature (see e.g., Geddes, 2022; Wollmann, 2018). I evaluate the observed fixed costs at the median values from the estimated identified set. Given these estimates, I recover ranges for the unobserved fixed cost ν_2 that are consistent with the moment inequalities for the endogenous firms. I take 100 random draws from a normal distribution with a mean and variance calibrated from these ranges and recover the pure strategy equilibria associated with each fixed cost realization. Additional details on how I compute equilibria of the model are available in Appendix D.

I define consumer surplus as an individual's expected certainty equivalent utility from enrolling in a plan. The literature has used similar measures of consumer welfare (see e.g.,

[34]In practice CSAs can span states. The service areas defined in model do not span states. As a result, I focus on CSA groupings of counties within a state if the CSA spans multiple states.

Einav et al., 2013; Ho and Lee, 2022). Thus the consumer surplus for individual i is:

$$CS_{imt} = \int \frac{1}{-\alpha_i} \log\left[1 + \sum_{j\in\mathcal{J}_{mt}} \exp(U^{CE}_{ijmt})\right] dF \tag{28}$$

where dF denotes the distribution of unobserved heterogeneity in the health states and moral hazard and α_i is the marginal utility of income. The certainty equivalent utility U^{CE}_{ijmt} is discussed in Appendix B.

I define net welfare (NW) as the sum of consumer surplus (CS) and firm profits (Π) net of government spending on Traditional Medicare and Medicare Advantage (G_{TM} and G_{MA} respectively):

$$NW = CS + \Pi - (G_{TM} + G_{MA}) \tag{29}$$

VII.B Model assumptions

The results presented in this section inform how features of my model impact equilibrium outcomes. To do this, I simulate the effect of lowering payments made to Medicare Advantage plans, a common counterfactual exercise in the literature. I start by simulating the equilibria of the model under status quo policies. I then simulate the effects of a policy change for models with different levels of restrictiveness to see how the model's predictions change. The most restrictive model holds firm entry and product offering decisions as fixed and holds marginal cost fixed at the market level. The less restrictive model allows firm costs to endogenously depend on enrollment but continues to hold firm participation decisions fixed. The exercise concludes with the full model, which has both endogenous costs and participation decisions. Each version of the model averages over draws from the Stage 2 shock distribution.[35]

Table 7 presents results for a simulation that lowers Medicare Advantage benchmarks

[35] Appendix Table E.7 does a similar exercise without using expected profits and holds unobservable shocks fixed at their observed values. Results are similar and consistent with comparable policy simulations in the literature.

by \$1,200 annually (\$100 per beneficiary-month). The first two columns report predictions from the full model with endogenous costs and firm participation under the current policy environment. The first column reports the average value across all equilibria of the model, while the second column reports the minimum and maximum across all the equilibria. These predicted outcomes are inclusive of the observed outcomes for the Massachusetts service area in 2018. The next column uses a model with constant marginal costs and fixed participation decisions ("Most Restrictive") to simulate the impact of the benchmark reduction. Consistent with prior work, I find that reducing benchmarks leads to lower enrollment in Medicare Advantage plans, and by extension, consumer surplus and firm profits. This effect primarily manifests through a higher premiums. Following the benchmark reduction, strategic firms increase their premiums from about \$660 annually to \$1,070 for HMOs. A similar increase occurs for the PPO plans. Due to the high level of consumer price sensitivity (elasticity), the higher premiums discourage MA enrollment in favor of the public option. The individuals that left MA for TM were higher cost, so average MA utilization declines. However, these individuals were relatively healthier than the TM population leading average TM utilization to fall. The third column reports predictions from the model with endogenous costs but fixed participation ("Less Restrictive"). Relative to the Most Restrictive model, MA enrollment falls and average MA utilization falls. This effect highlights the role of selection within the model. Under the Most Restrictive model, firms set premiums based on a market average risk adjusted cost that does not vary with enrollment. This feature allowed the strategic HMO plan to charge lower premiums. Once the firm becomes exposed to those costs, it must raise premiums to remain profitable. This action again leads to relatively sicker people leave MA for TM. These higher premiums translate to lower consumer surplus.

The last two columns report results for the model that allows firms to alter their product offerings and entry decisions ("Least Restrictive"). The fifth column reports the average value across all model equilibria while the final column reports the range of values across all equilibria. Relative to models with fixed entry decisions, the entry model predicts the total number of markets entered falls, as does the average number of strategic plans and markets entered per plan. This behavior is consistent with cream skimming and quantifiable by the fall in the average benchmark for strategic HMO plans relative to the models with fixed entry decisions. Despite the change in entry patterns, average MA utilization and enrollment increases. These patterns are the demand responses to endogenous firm product offerings. Under the prior models only a low generosity HMO is offered. For certain realizations of fixed costs it is optimal for the firm to offer the high generosity HMO as well. Consumers value this product, leading them to enroll when it enters the market and consume more healthcare due to its more generous cost sharing. Consistent with the increase in the size of the market, the Least Restrictive model also predicts the highest level of overall government spending and lowest net welfare. This pattern highlights how endogenous firm entry and product offering decisions may undercut savings from policy simulations that hold market participation as fixed.

Each model predicts a decline in consumer surplus and total government spending as a result of this policy change. Prior to the policy change, average consumer surplus was roughly \$317.71 million and total government spending was just under \$4.87 billion. Under the most restrictive policy, which has the smallest predicted MA enrollment, consumer surplus and government spending fall to just roughly \$20.74 million and \$3.96 billion respectively. In other words, an 18% reduction in government spending leads to a 93% reduction in consumer surplus. The impact of the policy on consumer surplus is attenuated somewhat as model assumptions are relaxed. Under the least restrictive model, the average predicted values for consumer surplus and government spending are \$23.66 million and \$3.97 billion, respectively. These values translate to a 18.5% reduction in government spending and an 93% decrease in consumer surplus relative to the status quo. One conclusion from this exercise is that the costs of subsidizing the private market do not translate into commensurate consumer welfare gains.

Another observation is that entry is only marginally impacted by changes to the supply subsidy. This finding suggests that firm fixed costs are not substantial barriers for participation. This effect may be driven in part by the set of potential entrants containing firms already in the health insurance market. It is possible that firms not already in the health insurance business may enter and have higher fixed costs. However, this is not typically observed and not a first-order concern. Moreover, the government is seeking to leverage private sector expertise in this market, so entry of a non-existing health insurance firm is unlikely to deliver these benefits for the government.

These simulations underscore the close connection between selection and consumer price sensitivity in my model. MA plans can attract more enrollment when they are able to operate profitably without charging consumers high premiums. These conditions are satisfied when the government heavily subsidizes plans or MA plans target markets where the plan can increase its subsidy payments. These channels are important for understanding the mechanisms behind the results in the next section that explore the effects of alternate subsidy systems.

VII.C Alternative subsidy policies

In this section, I use the model to explore the effects of alternative subsidy policies that could be used to regulate a competitive insurance market. These exercises assess the strength of the private market and whether these policies can improve its functioning in terms of lowering costs to the government. The results are presented in Table 8. The first column simulates the effects of the current system where firms are directly compensated for each beneficiary they enroll and the size of the payment is adjusted by the beneficiary's risk score. These values are the same as what appeared in the previous table.

The first counterfactual I consider is a system where no subsidy is provided to firms. Under this scenario, the government allows private firms to offer insurance plans that meet quality thresholds but the plans receive no other assistance. I find that absent subsidies, the private market unravels. Private plan entry is possible for some realizations of fixed cost shocks but the plans set premiums so high that consumers opt to remain in TM—the average annual HMO and PPO premiums are over \$8,000 and \$12,000 respectively. This counterfactual predicts the lowest amount of government spending and consumer surplus. Relative to the average outcome under the status quo policy, total government spending falls by roughly 13% and consumer surplus falls 100%. This is driven in part by the normalization for utility of enrolling in TM. These results illustrate the strength of the competition private firms face from TM in this setting. Despite offering more generous insurance plans than TM, absent a subsidy there is no premium private firms could charge that would cover their costs and attract any enrollment. Thus, the government must provide some support for this market to sustain its existence.

The second alternative system is presented in column 3 of Table 8. Under this policy, consumers receive an untargeted subsidy to purchase MA plans if they opt out of TM. The only revenue firms collect is in the form of premiums paid by beneficiaries that enroll in their plans. The size of the untargeted subsidy is equal to the average subsidy paid to firms observed in the data—roughly \$786 (\$9,430) per beneficiary-month (-year). Relative to the baseline scenario, this policy encourages more entry by the strategic plans. Average MA penetration grew from roughly 17% in the baseline scenario to about 29.5%. This growth in the market is driven by the efficiency of the low generosity PPO plan, which has relatively low supplemental revenue costs. As a result, this plan effectively becomes "free" for consumers with low health needs and enables it to compete more effectively against the public option. This sorting pattern is apparent when looking at how utilization marginal costs change. Under this policy, average MA utilization per-beneficiary falls from \$3,260 annually to \$2,290 annually, while average TM utilization increases to nearly \$6,000 annually, relative to an average of roughly \$5,300 annually in the baseline.

The untargeted demand subsidy increases welfare and government spending. Consumer surplus almost doubles relative to the status quo policy and firm profits are 2.5 times larger.

The growth in consumer surplus is consistent with the large cash transfer individuals receive from the government under the policy. The growth of firm profits is consistent with the market expansion primarily driven by healthier seniors with lower healthcare costs. These gains come at the cost of large increases in government spending. Average total government spending rises from \$4.87 billion to \$5.52 billion (13% increase). This change in spending is driven by a 56% increase in MA spending and is not offset by reductions in TM spending, which falls by just under 4%. Given this large increase in government spending, the policy has the lowest net welfare, despite significantly increasing consumer surplus and firm profits.

These results indicate how Medicare Advantage is not fully capturing the expertise of private firms in controlling healthcare utilization. Under the baseline and untargeted subsidy policies, MA attracts healthier enrollees than TM. This sorting arises because healthier consumers are the least sensitive to premiums. The healthier types then benefit from utilizing healthcare at lower costs than what they would pay under TM. Neither policy is wholly effective at offsetting consumer price sensitivity or attempting to target sicker populations to enroll in MA. However, each policy has distinct advantages—the supply subsidy gives firms a primary revenue source independent of premiums, while direct subsidies give consumers a clear incentive to enroll in MA. Risk adjustment also plays a role in the supply subsidy. Under current regulations, CMS adjusts payments based on each beneficiary's risk score. The scores are intended to capture differences in health relative to the typical TM beneficiary. However, the current risk score formula is failing to capture the true differences in utilization between healthy and sick seniors enrolled in TM and MA. Noisy risk scores distort firm entry incentives and can cause government spending to proliferate unnecessarily as MA firms enroll sicker beneficiaries.

The last policy I simulate draws from the strengths of both subsidy systems and eliminates the distortions they create. The targeted policy has three components. The first preserves supply subsidies but lowers cost benchmarks by \$1,200. The second piece passes along some of these savings to consumers in the form of a means tested subsidy. Low-income seniors receive a $600 payment if they enroll in a MA plan, while all other seniors get a $300 payment for enrolling in a MA. The third part generates risk scores that perfectly align a beneficiary's model expected healthcare utilization in MA to their utilization in TM. In general, this change results in relative increases in the risk scores for healthy individuals and decreases in the risk scores for sicker ones. This policy produces entry patterns similar to the baseline scenario. Average MA utilization falls, consistent with sicker beneficiaries shifting out of MA as HMO premiums rise in response to benchmark reductions. PPO plans have lower premiums under this policy and enroll more consumers than the strategic HMO plans. These effects are attenuated somewhat by the demand subsidizes, but the policy still produces a net increase in the premiums for HMO plans. Rising HMO premiums also explain why average consumer surplus falls by 19% and the size of MA market decreases to by 3.6 percentage points under this policy. However, the minimum values for consumer surplus and MA enrollment are 40% larger under this policy than the baseline. Notably, average total government spending under the targeted policy falls to $4.59 billion, the lowest of all policies I simulate.

Finally, I explore the distributional consequences of these policies in Table 9. The table reports consumer surplus under each counterfactual policy by observable beneficiary characteristics. Under the current policy, the oldest seniors as well as individuals with risk scores in the second and fourth quartile have the average highest surplus. This pattern likely reflects the value MA plans can deliver for these groups. For individuals with moderate health needs, MA provides lower costs in the form of more generous cost sharing. For the sickest individuals—who tend to be older—MA plans limit their medical bills by offering out-of-pocket maximums that do not exist in TM. The untargeted demand subsidy raises welfare for everybody, consistent with the uniform cash transfer. However, the healthiest individuals benefit the most as these individuals tend to be the least price sensitive and shift from TM to MA first. Under the targeted policy, low-income beneficiaries benefit the most—consistent with means tested demand subsidy. This policy also creates a more equitable distribution of consumer surplus across risk score quantiles.

VIII Conclusion

This paper studies competition and participation in Medicare Advantage insurance markets. I develop and estimate an equilibrium model of health plan supply and demand that captures the feedback among government policy, firm entry and product offering decisions, and consumer sorting and utilization of health insurance plans. My model accounts for multiple equilibria that may arise in firm decisions about which markets to enter and products to offer. I then use this model to assess the optimality of different government policies to regulate choice and competition in these markets.

My findings indicate policymakers face tradeoffs when deciding how to use private markets to deliver a public good like health insurance benefits. Subsidies are necessary to sustain the private market. However, current subsidy policy is not letting the program deliver on its stated goals. Medicare Advantage plans tend to attract healthier individuals to enroll and the current risk adjustment structure distorts the government's costs of subsidizing the market. Supply subsidies give firms more flexibility to set lower premiums and attract relatively sicker individuals into MA. Moreover, they are unable to bring in the sickest TM beneficiaries into the program, which may reflect MA plans still charging non-zero prices at current subsidy levels or switching costs seniors face when attempting to move out of TM. An untargeted demand subsidy increases MA enrollment but this policy disproportionately benefits healthier seniors that are not price sensitive. I find that a targeted policy that leverages the benefits of supply and demand subsidies is capable of delivering similar outcomes but at lower costs to the government. Additionally, the surplus this policy generates is distributed more equitably across health statuses. Policymakers must weigh these considerations when deciding which framework enables this private market to deliver value for consumers and state policy objectives.

Tables and Figures

Tables

Table 1: Market level summary statistics, 2017–2018

	Mean	SD	P10	P90
Monetary characteristics				
Premium	19.6	18.3	0.7	43.9
Base premium	0.6	2.7	0	0.8
Supplemental premium	18.9	17.2	0.7	42.9
Subsidy	750.0	47.2	695.1	808.7
Rebate	66.0	31.1	30.1	103.8
Benchmark	843.2	45.8	798.9	896.8
Average OOPC	140.5	16.6	119.9	160.5
Plan menus				
Firms	3	2	1	6
Plans	7	6	2	15
High generosity plans	2	3	0	6
HMOs	4	4.5	0	10
Market size	14,535	36,214	1,259	32,529
Plan enrollment	915	2,897	21.1	1,907
Market				
MA penetration	15.0	13.0	1.9	33.8
Market share	5.4	4.5	0.9	10.4
Market share | MA	46.7	25.8	18.4	92.2
HHI	195.8	309.5	2.6	541.3
HHI | MA	6,502.8	2,556.3	3,325.0	10,000

Notes: This table contain market-level summary statistics for the 4,845 markets in the analysis sample. Markets are defined as county-year pairs. Plan characteristics are weighted by within market enrollment. "Average OOPC" measures the average expected monthly out-of-pocket costs in a Medicare Advantage plan across health states. The "high generosity plans" earn this designation based on this cost measure.

Table 2: Benchmarks impact plan entry and choice set generosity, 2016–2018

	(1) Firms	(2) Plans	(3) Extra Coverage	(4) Rebate	(5) Supplemental Permium	(6) Supplemental Revenue
Avg Benchmark (LOO)	-0.001	0.005***	0.060**	0.111***	-0.015*	0.056***
	(0.001)	(0.002)	(0.029)	(0.016)	(0.009)	(0.011)
County FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Mean of Dep. Var.	2.76	5.75	274.03	53.41	17.63	51.76
R^2	0.94	0.96	0.88	0.89	0.85	0.86
Observations	6,970	6,970	6,970	6,970	6,970	6,970

Notes: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors clustered at the county-level. This table reports estimates from OLS regressions of the average plan benchmark onto market-level measures of plan generosity. An observation is a county-year. Monetary values are converted into 2008$. Benchmarks for each plan are constructed by taking the enrollment weighted average across all markets where a plan is present, leaving out the focal market. These plan level benchmarks are then aggregated to the market level as an enrollment weighted average "Avg Benchmark (LOO)." "LOO" stands for leave-one-out. Outcomes are calculated as within market enrollment weighted averages.

Table 3: Menu generosity predicts MA average annual utilization, 2017–2018

	(1)	(2)	(3)	(4)	(5)	(6)
Market Avg Rebate ($)	4.31***	6.76***	6.27***			
	(0.31)	(0.34)	(0.35)			
Prob Enroll Gen Plan				-53.25	220.64***	207.44***
				(81.61)	(88.38)	(90.01)
Year FE		✓	✓		✓	✓
Individual Controls		✓	✓		✓	✓
Market Controls		✓	✓		✓	✓
Plan Controls			✓			✓
Mean of Dep. Var.	8,415.18	8,415.18	8,415.18	8,415.18	8,415.18	8,415.18
Observations	6,309,253	6,309,253	6,309,253	6,309,253	6,309,253	6,309,253

Notes: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Robust standard errors are in parentheses. This table reports estimates from OLS regressions of observable individual, market, and plan characteristics onto average annual healthcare utilization measured in standardized dollar units proposed by Jung et al. (2022). "Market Avg Rebate" measures the average rebate paid to all Medicare Advantage plans in a beneficiary's market. "Prob Enroll Gen Plan" measures the probability of enrolling in a high generosity plan based on market shares. Individual controls include their age and indicators for risk score quantiles, female, and low income status. Market controls include measures of how rural the county is, the share of the population with a college degree, the mortality rate of the Medicare population, and the share of the Medicare population that is eligible for Medicaid. Plan controls include indicators for star ratings (at half star intervals) and whether the plan is a HMO.

Table 4: Demand estimates and model implied quantities

			Estimate	95% CI
Demand	Premium (α_i)	Mean	-12.59	[-13.09, -12.08]
		Low income	-3.55	[-3.79, -3.30]
	Utilization utility (β_i)	Mean	11.57	[11.07, 12.07]
		Low income	-0.15	[-0.17, -0.13]
		Contract	✓	
	Fixed effects (θ_2)	Year	✓	
		Star rating	✓	
Quantities	Moral hazard (ω_i)	TM	14.69	[14.46, 14.90]
	Pct. change in utilization	PPO-Low	5.83	[5.78, 5.90]
	from 100% to 0% coins.	PPO-High	5.50	[5.44, 5.65]
		HMO-Low	6.97	[6.92, 6.99]
		HMO-High	5.31	[5.14, 5.47]
	Utilization costs (ϕ)	TM	0.15	[0.14, 0.15]
	($1,000)	PPO	1.23	[1.21, 1.24]
		HMO	1.61	[1.60, 1.62]
	Switching costs (ι)	Coefficient	-8.62	[-8.87, -8.37]
	($1,000)	Mean	0.68	[0.68, 0.69]
		Low income	0.53	[0.53, 0.54]
	Risk aversion (ψ)	CARA coefficient ($\times 10^{-5}$)	1.08	[0.57, 2.04]
	($)	Cohen and Einav (2007) gamble	99.89	[99.80, 99.94]
Beneficiary-year observations			73,941,784	
Plan-year observations			3,702	

Notes: This table reports estimates for demand parameters and quantities implied by the demand and healthcare utilization model. 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. Detailed parameter estimates and standard errors are available in Appendix Table E.5.

Table 5: Fixed cost identified set estimates

	Identified set
Number of plans	[612.7, 1,333.1]
Existing network	
Total hospital systems	[110.5, 252.0]
Total doctors	[1.5, 2.2]
No network	
Total hospital systems	[515.7, 981.6]
Total doctors	[6.2, 9.0]
Moment inequalities	124

Notes: This table reports the estimated identified set for the fixed cost parameters. Costs are reported in $1,000 units. Sets are constructed by inverting the test statistics from Chernozhukov et al. (2019). The self-normalized one step procedure is used with $\alpha = 0.05$.

Table 6: Summary of Massachusetts Medicare Market, 2018

			Market share	
Firm	Offered plans	Markets	All	MA only
Tufts Health Plan	HMO (L-H)	8	3.38	32.90
Blue Cross-Blue Shield of Mass.	PPO (L-H), HMO-H	11	2.38	23.21
United Health	HMO (L-H)	7	2.03	19.74
Baystate Health	HMO (L-H)	4	1.03	10.08
Harvard Pilgrim	HMO (L-H)	7	0.68	6.64
Fallon Community	HMO (L-H)	4	0.66	6.40
Aetna	PPO-L, HMO-L	7	0.11	1.02
Medicare Advantage		12	10.26	–
Traditional Medicare		14	89.74	–
Total markets/beneficiaries		14	790,406	81,086

Notes: This table reports the observed market structures for Massachusetts in 2018.

Table 7: Impact of modeling choices on equilibrium outcomes

	No change		Cut benchmarks $1,200			
	Least Restrictive		Most Restrictive	Less Restrictive	Least Restrictive	
Strategic firms						
Markets entered	12.18	[6, 14]	11	11	9.86	[0, 14]
Plans entered	3.38	[1, 4]	3	3	2.87	[0, 4]
Enrollment (1,000)	89.79	[6.16, 97.68]	8.29	4.19	9.75	[0, 15.18]
Enrollment share (%)	11.36	[0.78, 12.36]	1.05	0.53	1.23	[0, 1.92]
Markets entered by plan	8.94	[3, 10.25]	10	10	7.56	[0, 11]
Utilization marginal costs ($1,000)	3.61	[2.40, 4.29]	2.08	1.82	3.15	[0, 4.01]
HMO premium ($1,000)	0.66	[0.22, 0.80]	1.07	1.25	1.29	[1.19, 1.34]
PPO premium ($1,000)	0.16	[0, 3.41]	1.09	1.25	1.54	[0, 9.43]
HMO benchmark ($1,000)	10.65	[10.38, 10.66]	9.45	9.45	9.38	[8.76, 9.46]
PPO benchmark ($1,000)	10.51	[9.96, 10.66]	9.38	9.38	9.40	[8.76, 9.46]
All products						
MA share (%)	16.99	[8.64, 17.75]	1.34	0.86	1.57	[0.36, 2.25]
MA utilization ($1,000)	3.26	[2.58, 3.44]	1.57	1.29	2.45	[0.41, 3.33]
TM utilization ($1,000)	5.27	[5.13, 5.29]	4.97	4.96	4.96	[4.94, 4.97]
Welfare						
Profit ($1,000)	78,610	[3,724, 95,959]	3,077	1,390	8,284	[49, 12,739]
Consumer surplus ($1,000)	317,707	[128,619, 335,538]	20,736	12,219	23,663	[2,198, 35,296]
Government MA spending ($1,000)	1,412,728	[663,223, 1,473,622]	87,347	49,491	113,415	[16,315, 166,274]
Government TM spending ($1,000)	3,454,931	[3,437,806, 3,707,534]	3,874,476	3,883,059	3,856,871	[3,838,264, 3,891,203]
Total government spending ($1,000)	4,867,660	[4,370,757, 4,911,428]	3,961,823	3,932,550	3,970,286	[3,907,518, 4,004,538]
Net welfare ($1,000)	-4,471,343	[-4,515,742, -4,238,415]	-3,938,010	-3,918,941	-3,938,836	[-3,962,060, -3,905,320]

Notes: This table reports how simulated quantities from the model change as different features are added. The first two columns report predicted outcomes from a model where marginal costs and firm participation decisions are endogenous ("Least Restrictive"). The first column reports the average value across all model equilibria while the second column reports the minimum and maximum across all equilibria. The other columns simulate the impacts of cutting Medicare Advantage benchmarks by $1,200 annually. The third column reproduces predicted from a model where marginal costs and firm participation decisions are fixed ("Most Restrictive"). The fourth column allows selection to impact firm costs while holding entry decisions fixed ("Less Restrictive). The final columns reports predictions from the Least restrictive model. The top panel produces quantities for the endogenous firms. The middle panel reports Medicare Advantage penetration and average per beneficiary utilization in MA and TM. The bottom panel reports welfare relevant metrics in levels. "HMO (PPO) premium" and "HMO (PPO) benchmark" report the average premium and benchmark across the strategic plan-type offerings.

Table 8: Equilibrium outcomes under alternative subsidy systems

	Baseline		No subsidy		Untargeted		Targeted	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range
Strategic firms								
Markets entered	12.18	[6, 14]	13.51	[0, 14]	14	[14, 14]	12.26	[8, 14]
Plans entered	3.38	[1, 4]	3.54	[0, 4]	3.3	[1, 4]	3.48	[1, 4]
Enrollment (1,000)	89.79	[6.16, 97.68]	0	[0, 0]	160.31	[154.20, 163.59]	60.28	[26.01, 70.78]
Enrollment share (%)	11.36	[0.78, 12.36]	0	[0, 0]	20.28	[19.51, 20.70]	7.63	[3.29, 8.96]
Markets entered by plan	8.94	[3, 10.25]	8.87	[0, 14]	10.72	[6.67, 14]	8.88	[5, 11]
Utilization marginal costs ($1,000)	3.61	[2.40, 4.29]	0.09	[0, 4.09]	1.47	[1.41, 1.51]	1.95	[0.98, 3.06]
HMO premium ($1,000)	0.66	[0.22, 0.80]	7.16	[6.67, 10.52]	10.37	[9.96, 11.61]	1.08	[0.59, 1.49]
PPO premium ($1,000)	0.16	[0, 3.41]	5.22	[0, 11.28]	8.60	[8.59, 8.6]	0.08	[0.03, 0.15]
HMO benchmark ($1,000)	10.65	[10.38, 10.65]	10.54	[9.96, 10.65]	10.53	[9.96, 10.65]	9.42	[8.76, 9.45]
PPO benchmark ($1,000)	10.50	[9.96, 10.65]	10.53	[9.96, 10.65]	10.57	[10.57, 10.57]	9.37	[8.76, 9.45]
All products								
MA share (%)	16.99	[8.64, 17.75]	0	[0, 0]	29.45	[28.76, 29.83]	13.40	[9.81, 14.53]
MA utilization ($1,000)	3.26	[2.58, 3.44]	0.10	[0.02, 4.08]	2.29	[2.27, 2.30]	2.53	[2.23, 3.01]
TM utilization ($1,000)	5.27	[5.13, 5.29]	4.93	[4.93, 4.93]	5.96	[5.93, 5.98]	5.28	[5.15, 5.31]
Welfare								
Profit ($1,000)	78,610	[3,724, 95,959]	0.0	[0.0, 0.0]	198,979	[138,877, 212,654]	49,023	[1,254, 64,086]
Consumer surplus ($1,000)	317,707	[128,619, 335,538]	0.0	[0.0, 0.0]	622,244	[602,352, 633,047]	257,311	[180,409, 281,447]
Government MA spending ($1,000)	1,412,728	[663,223, 1,473,622]	0.0	[0.0, 0.0]	2,195,536	[2,144,082, 2,223,515]	979,673	[721,509, 1,066,241]
Government TM spending ($1,000)	3,454,931	[3,437,806, 3,707,534]	3,893,210	[3,893,210, 3,893,210]	3,323,344	[3,314,229, 3,339,839]	3,611,663	[3,583,972, 3,686,501]
Total government spending ($1,000)	4,867,660	[4,370,757, 4,911,428]	3,893,210	[3,893,210, 3,893,210]	5,518,880	[5,483,920, 5,537,744]	4,591,336	[4,392,472, 4,650,523]
Net welfare ($1,000)	-4,471,343	[-4,515,742, -4,238,415]	-3,893,210	[-3,893,210, -3,893,210]	-4,697,657	[-4,765,876, -4,671,342]	-4,285,002	[-4,334,646, -4,194,214]

Notes: This table reports how simulated equilibrium outcomes change as the delivery system for Medicare Advantage subsidies changes. For each simulation the "Range" column reports the minimum and maximum value across all the recovered equilibria of the model, while the "Mean" column reports average value across equilibria. "Baseline" refers to the current system, which is a supply side subsidy that is scaled by a beneficiary's risk score. "No subsidy" refers to a system where the government does not provide any subsidy to Medicare Advantage plans but regulates the plans meet their minimal coverage standards. "Untargeted" simulates a system that gives the observed enrollment weighted average risk adjusted pre-beneficiary subsidy for Massachusetts (approximately $9,432 per year) to consumers to offset the costs of a Medicare Advantage plan. "Targeted" cuts CMS cost benchmarks by $1,200, offers a demand subsidy of $600 to low income beneficiaries that enroll in Medicare Advantage plans and $300 for non-low income MA enrollees, and replaces CMS calculated risk scores with risk scores implied by the model based on the ratio of expected MA healthcare utilization and TM utilization. "HMO (PPO) premium" and "HMO (PPO) benchmark" report the average premium and benchmark across the strategic plan-type offerings.

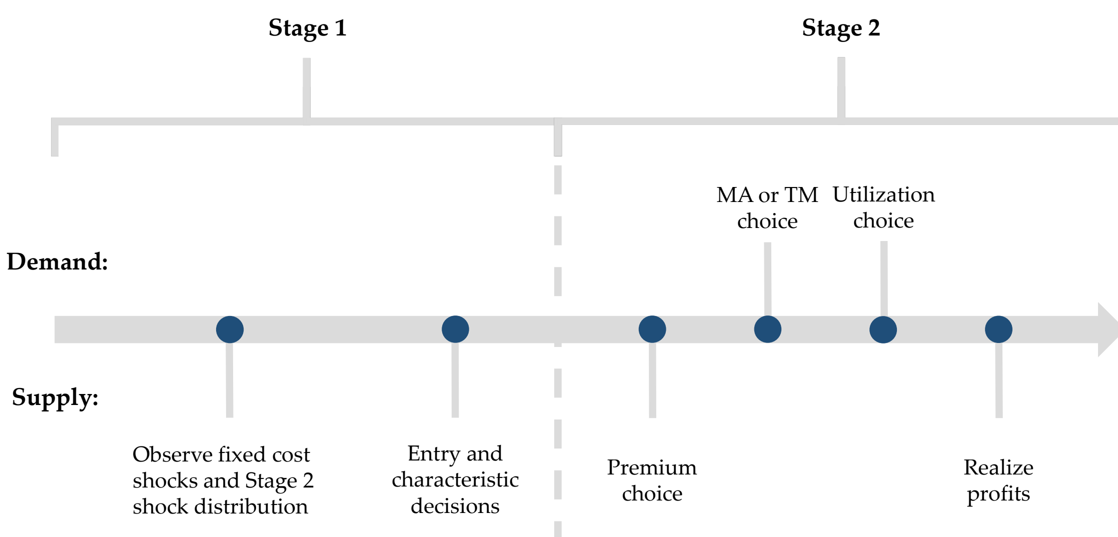
Table 9: Consumer surplus by observables under alternative subsidy systems

	Baseline		Untargeted		Targeted	
	Mean	Range	Mean	Range	Mean	Range
Age $\geq$ 86	0.43	[0.18, 0.45]	0.65	[0.62, 0.67]	0.31	[0.22, 0.35]
Female	0.40	[0.16, 0.42]	0.79	[0.76, 0.80]	0.33	[0.23, 0.36]
Low income	0.27	[0.09, 0.28]	0.82	[0.80, 0.83]	0.56	[0.44, 0.60]
High Medicaid county	0.40	[0.19, 0.42]	0.81	[0.78, 0.83]	0.35	[0.26, 0.38]
Risk score Q1	0.37	[0.17, 0.40]	0.94	[0.92, 0.95]	0.33	[0.21, 0.35]
Risk score Q2	0.42	[0.16, 0.44]	0.82	[0.79, 0.83]	0.31	[0.21, 0.34]
Risk score Q3	0.39	[0.15, 0.41]	0.77	[0.75, 0.78]	0.32	[0.21, 0.35]
Risk score Q4	0.43	[0.18, 0.44]	0.65	[0.62, 0.67]	0.35	[0.25, 0.38]

Notes: This table reports how consumer surplus is distributed across observable characteristics under different subsidy policies. For each simulation the "Range" column reports the minimum and maximum value across all the recovered equilibria of the model, while the "Mean" column reports average value across equilibria. "Baseline" refers to the current system, which is a supply side subsidy that is scaled by a beneficiary's risk score. "Untargeted" simulates a system that gives the observed enrollment weighted average risk adjusted pre-beneficiary subsidy for Massachusetts (approximately \$9,432 per year) to consumers to offset the costs of a Medicare Advantage plan. "Targeted" cuts CMS cost benchmarks by \$1,200, offers a demand subsidy of \$600 to low income beneficiaries that enroll in Medicare Advantage plans and \$300 for non-low income MA enrollees, and replaces CMS calculated risk scores with risk scores implied by the model based on the ratio of expected MA healthcare utilization and TM utilization.

Figures

Figure 1: Model summary

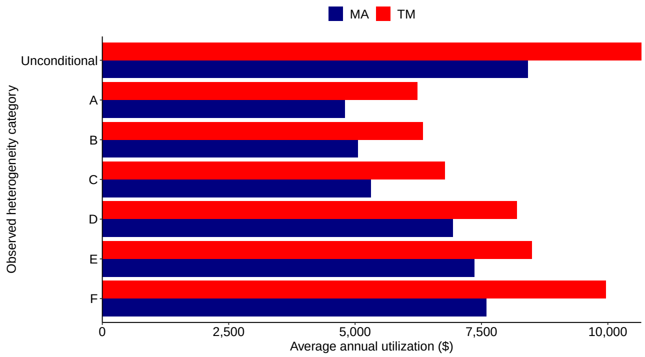


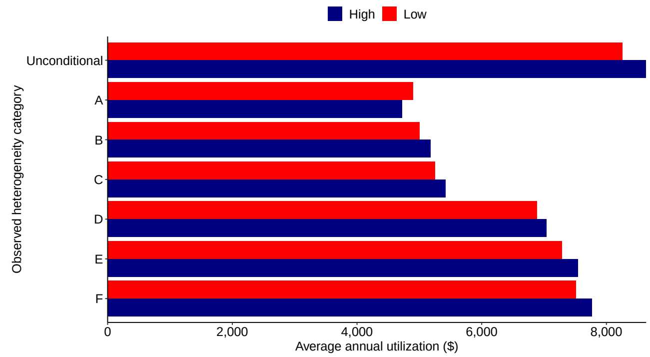
Notes: This figure summarizes the timing and decisions made in the model. Firm decisions are below the central line and correspond to the supply side of the model. Beneficiary decisions are above the central line and correspond to the demand side of the model.

Figure 2: Average Healthcare Utilization, 2017–2018

(a) TM vs. MA

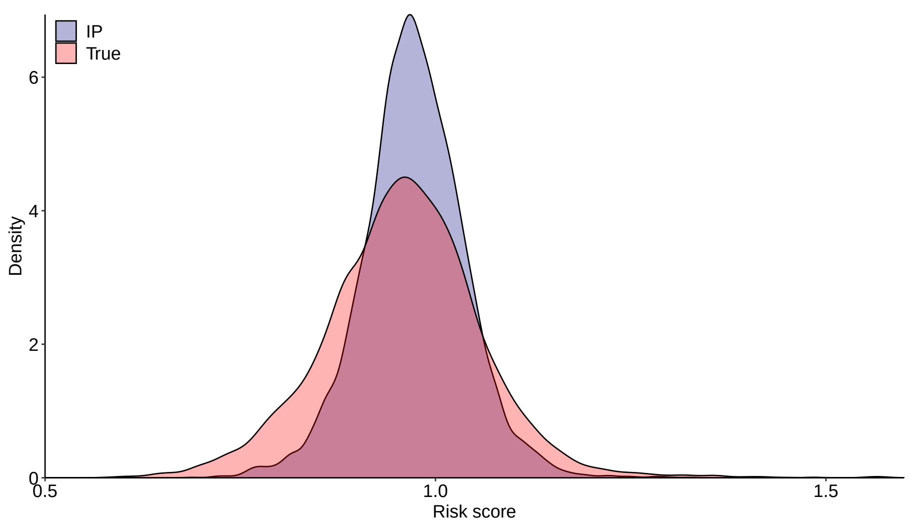
(b) High vs. Low Generosity MA Plans





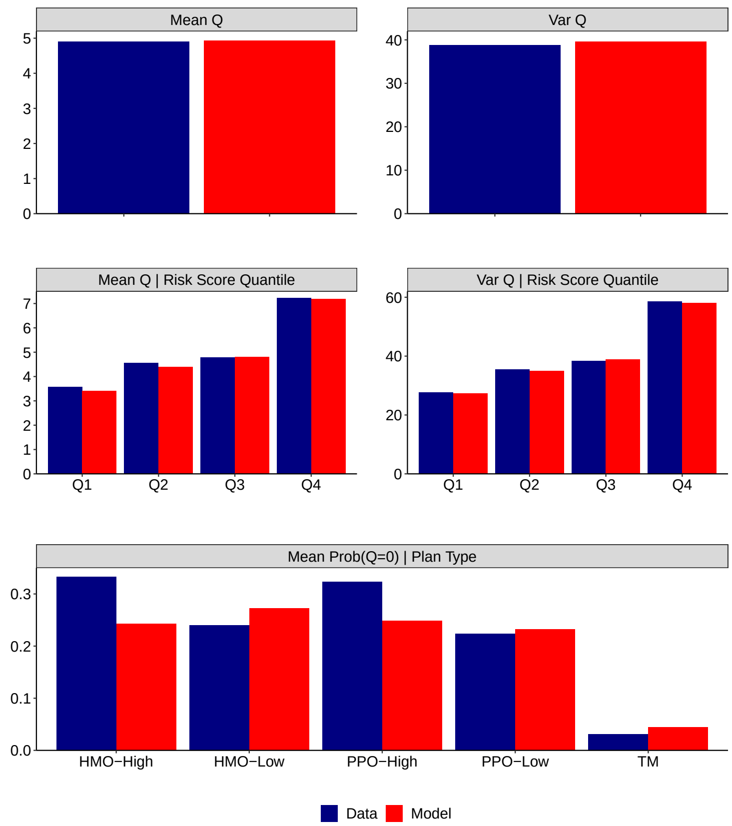
Notes: This figure compares the average annual healthcare utilization of Medicare beneficiaries. The averages are presented unconditionally and for the six most common groupings observable heterogeneity. Observable categories summarize a beneficiary's risk score, age, gender, income, and their county's Medicare mortality and Medicaid eligibility rates. These groupings are constructed by converting risk scores into quantiles and defining all possible combinations of these characteristics.

Figure 3: Average market risk scores 2017–2018



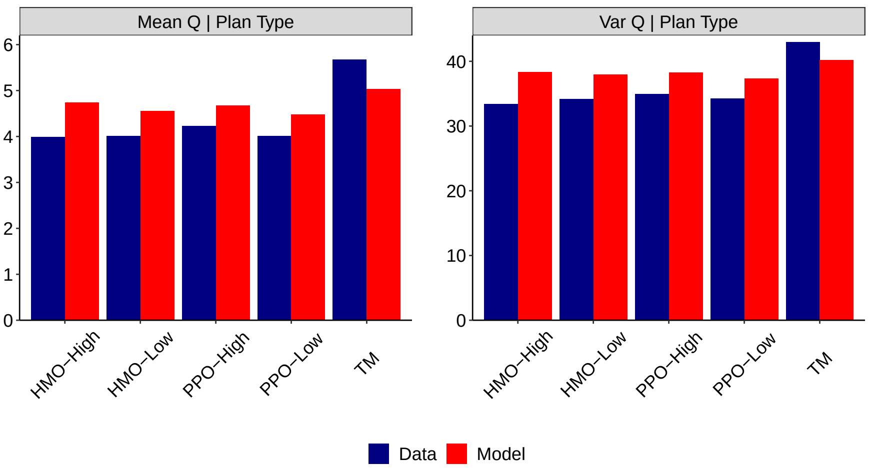
Notes: This figure compares the distribution of risk scores at the market-level. Markets are defined as a county-year pair. The red distribution is the true risk score reported by CMS. The blue distribution comes from the risk scores that I calculate using only inpatient diagnoses. These individual risk scores are averaged across all beneficiaries in the market to construct the distribution.

Figure 4: Targeted moment fit



Notes: This figure plots a subset of the targeted moments used to estimate the health state distribution and demand parameters. The targeted moments included in the figure are the unconditional mean and variance of the utilization distribution, the mean and variance of the utilization distribution conditional on risk score quartiles, and the probability of utilizing no healthcare conditional on plan type.

Figure 5: Untargeted moment fit



Notes: This figure plots untargeted data moments and their model analogs. The moments included in the figure are the mean and variance of healthcare utilization conditional on plan type.

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SUPPLEMENTAL APPENDIX

Entry and Competition in Insurance Markets: Evidence from Medicare Advantage

Matthew V. Zahn*

November 22, 2023

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

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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.

$$r_{it} = [\underbrace{R_{it}(\text{HCC Model}_t)}_{\substack{\text{Base} \\ \text{score}}} / \underbrace{NF_t}_{\substack{\text{TM} \\ \text{normalization}}}] \cdot 1\{\text{MA bene } t-1\} \underbrace{CPA_t}_{\substack{\text{Coding pattern} \\ \text{adjustment}}} \tag{A.30}$$

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.30). 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

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

or TM can be expressed as a function of the amount of healthcare the beneficiary chooses 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

[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.

Advantage plans. In general, Traditional Medicare tends to have higher costs because of 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:

$$\begin{bmatrix} \bar{\mu}_{its} \\ \log \omega_{is} \end{bmatrix} = \begin{bmatrix} \mathbf{X}_{it}^{\mu} \boldsymbol{\beta}^{\mu} \\ \mathbf{X}_{i}^{\omega} \boldsymbol{\beta}^{\omega} \end{bmatrix} + d_s \cdot \text{chol}\left(\begin{bmatrix} \sigma_{\mu}^2 & \\ \sigma_{\mu,\omega}^2 & \sigma_{\omega}^2 \end{bmatrix} \right) \tag{B.31}$$

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:

$$h_{itsb} = \exp(\bar{\mu}_{its} + d_b \underbrace{\mathbf{X}_{it}^{\sigma} \boldsymbol{\beta}^{\sigma}}_{=\sigma_{h,it}}) \tag{B.32}$$

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:

$$\hat{Q}^*_{ijts} = \sum_{b=1}^{n_b} W_b \cdot \hat{Q}^*_{ijtsb} \tag{B.33}$$

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 $\hat{Q}^*_{ijt}$:

$$\hat{Q}^*_{ijt} = \sum_{s=1}^{n_s} W_s \cdot s_{ijmts} \cdot \hat{Q}^*_{ijts} \tag{B.34}$$

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}):

$$U^{CE}_{ijmts} = \bar{l}_{ijmts} - \frac{1}{\psi} \log \left(\sum_{b=1}^{n_b} W_b \cdot \exp[-\psi(l_{ijmts}(h_{itsb}) - \bar{l}_{ijmts})] \right) \tag{B.35}$$

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:

$$s_{ijmts} = \frac{\exp(U^{CE}_{ijmts})}{1 + \sum_{\ell \in \mathcal{J}_{mt}} \exp(U^{CE}_{i\ell mts})} \tag{B.36}$$

$$s_{ijmt} = \sum_{s=1}^{n_s} W_s \cdot s_{ijmts} \tag{B.37}$$

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:

$$s_{jmt} = \sum_{i=1}^{M_{mt}} W_{imt} \cdot s_{ijmt} \tag{B.38}$$

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:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{M}(\theta)' \mathcal{W} \mathcal{M}(\theta) \tag{B.39}$$

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.39). 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.39).

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)):

$$m_j(\theta) = \Delta^- F(m, m') - \Delta^+ \sum_{\mathcal{J}_A} \mathbb{E}\,\Pi(m, m') - \Delta^+ \nu_1(m, m') \leq 0 \tag{B.40}$$

The mean and standard deviations for moment k are:

$$\varphi_k = \frac{1}{D} \sum_{d=1}^{D} m_{kd}(\theta) \qquad \varsigma_k = \sqrt{\frac{1}{D} \sum_{d=1}^{D} (m_{kd} - \varphi_k)^2} \tag{B.41}$$

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

$$T = \max_{1 \leq k \leq K} \frac{\sqrt{D}\varphi_k}{\varsigma_k} \tag{B.42}$$

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

$$c(\alpha) = \frac{\Phi^{-1}(1 - \alpha/K)}{\sqrt{1 - \Phi^{-1}(1 - \alpha/K)^2/D}} \tag{B.43}$$

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:

$$B_{mt} = \alpha_0 + \alpha_1 \text{Post-ACA}_{mt} + \alpha_2 X_{mt} + \epsilon_{mt} \tag{C.44}$$

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.44) 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.44): 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:

$$Y_{mt} = \beta_m + \beta_t + \beta_0 B_{mt} + \sum_{i \in \{[2008,2017] \setminus 2011\}} \beta_i 1[t = i] B_{mt} + \epsilon_{mt} \tag{C.45}$$

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.

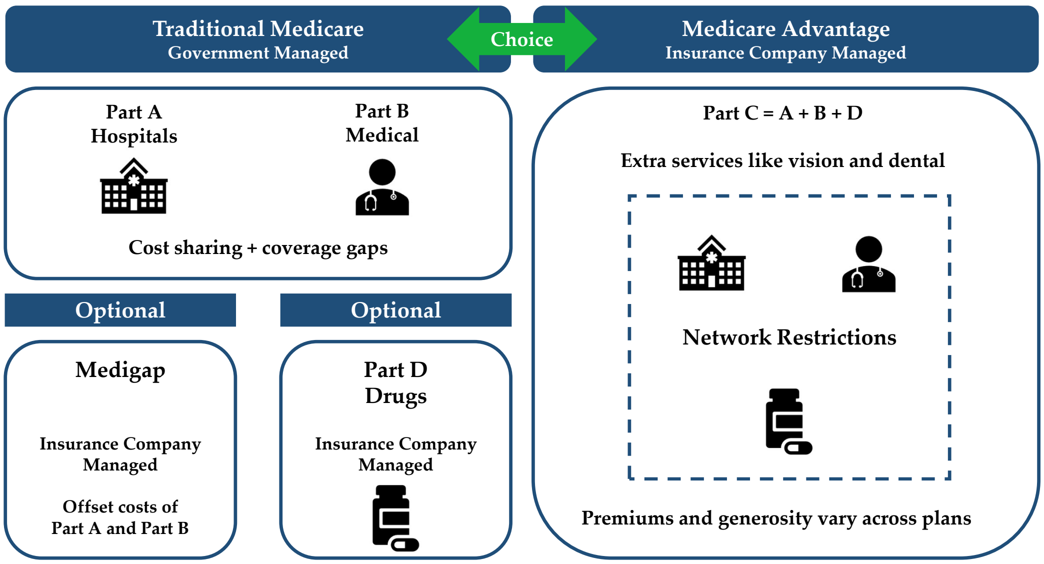
3. The second firm best responds to the $t-1$ plan menu that includes the first firm's best response. This process continues for each firm in the move order.

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

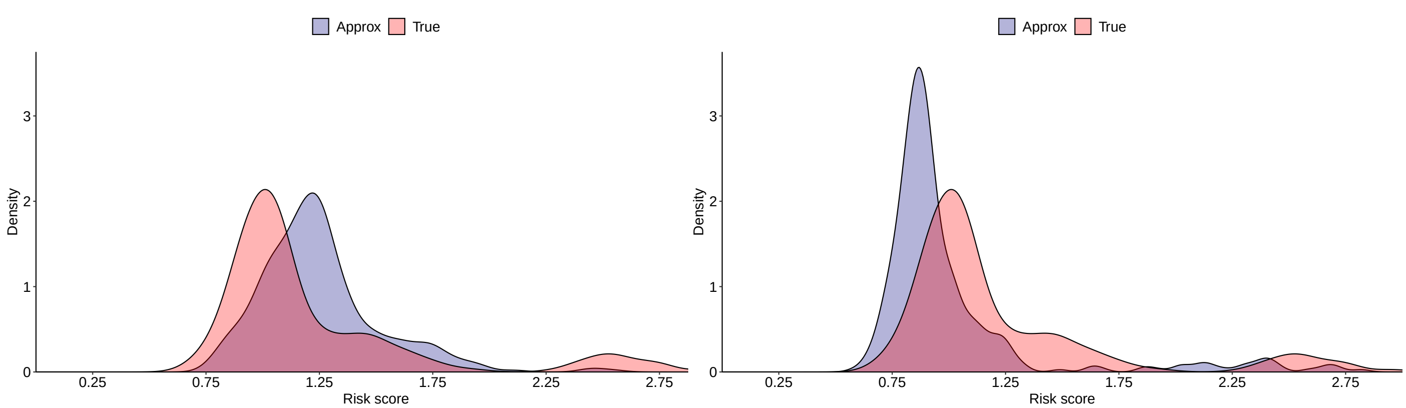


Notes: This figure summarizes the choices and tradeoffs Medicare beneficiaries face when making their annual health insurance coverage decisions.

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

(a) IP, OP, and Carrier Diagnoses

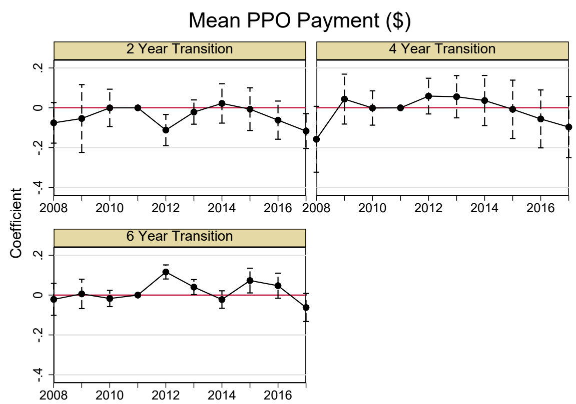
(b) IP Diagnoses



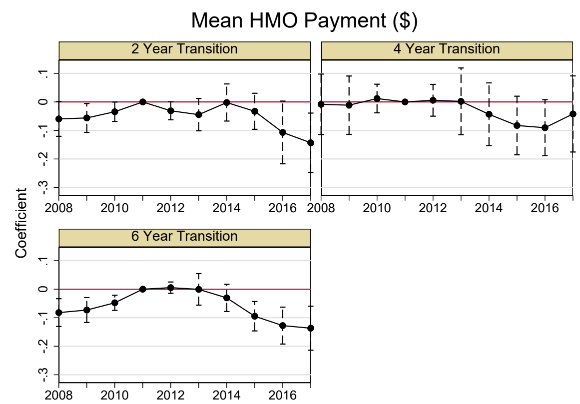
Notes: This figure compares the distribution of risk scores at the plan-level. The red distribution is the true risk score reported by CMS. The blue distribution comes from the risk scores that I calculate. The left panel uses diagnoses from inpatient, outpatient, and selected physician encounters and 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

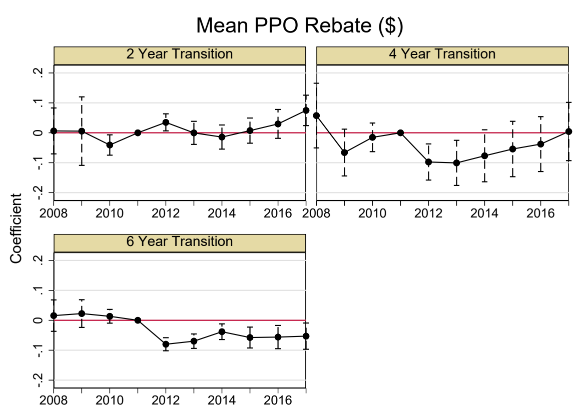
(a)



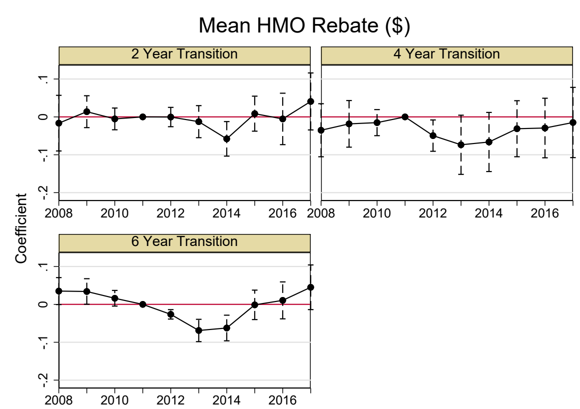
(b)



(c)



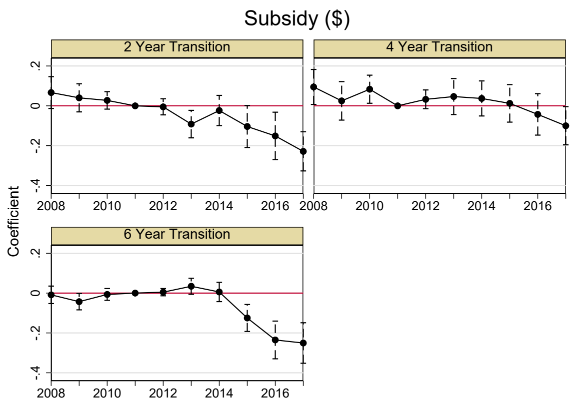
(d)



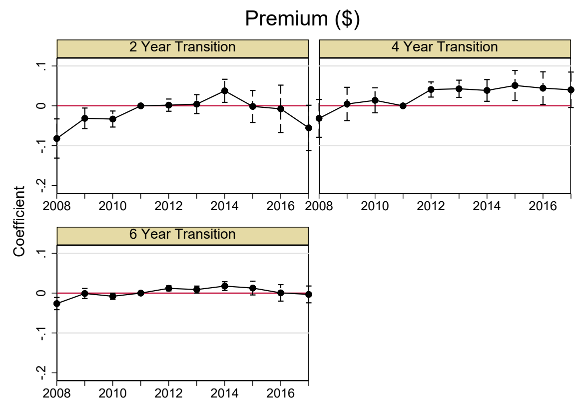
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on plan subsidy and rebate payments for HMO and PPO plans. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

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

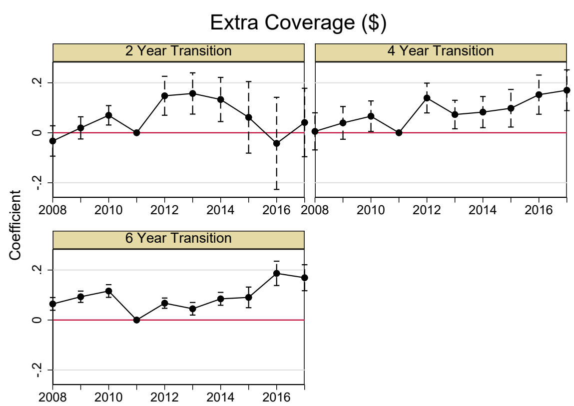
(a)



(b)



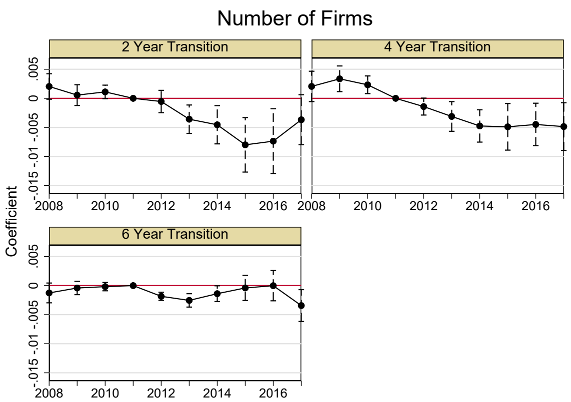
(c)



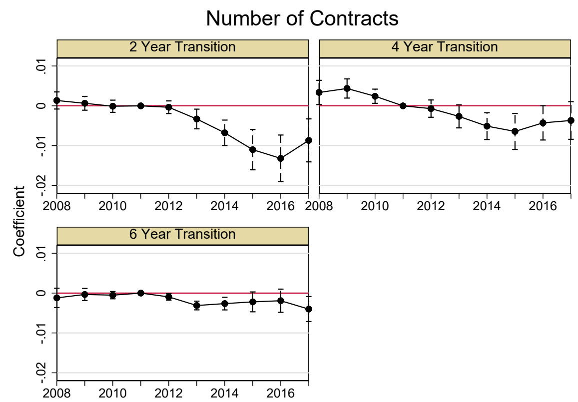
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on plan characteristics. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

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

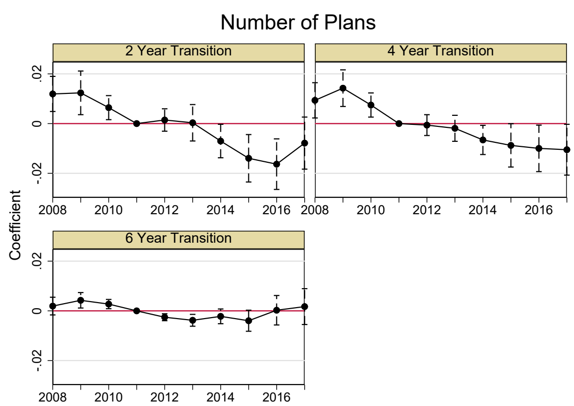
(a)



(b)



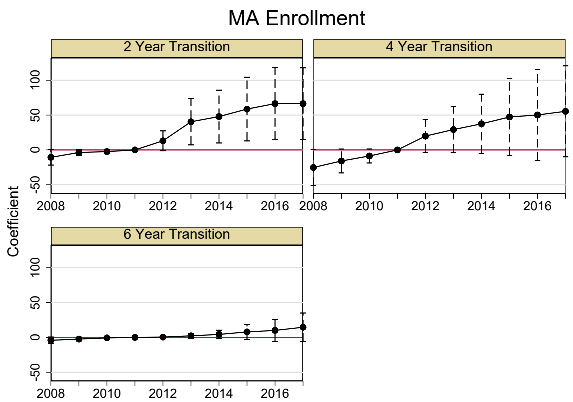
(c)



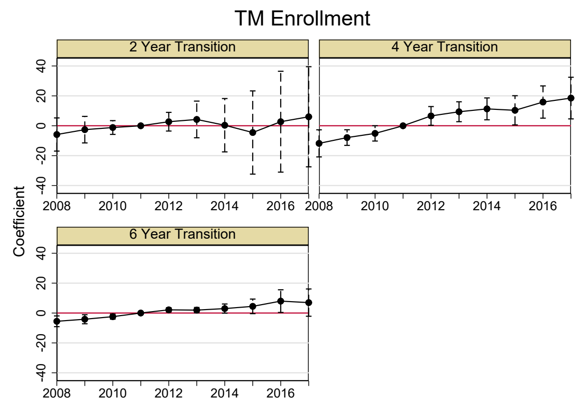
Notes: This figure plots the event study coefficients for the impact of ACA reductions to Medicare Advantage benchmarks on firm entry. Estimates are done separately by transition groups. An observation is a county-year. Dollar values are converted into 2008$.

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

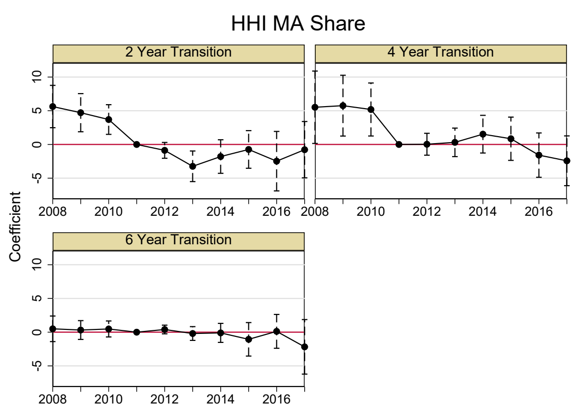
(a)



(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 ≠ 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
	$\mathrm{Corr}(\mu_h, \log \omega)$	-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.