Advertising Competition and Risk Selection in Health Insurance Markets: Evidence from Medicare Advantage*

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Job Market Paper

November 24, 2013

Abstract

This paper studies the incentives for private insurers to use advertising to attract low-cost, healthy individuals and the impacts of advertising on selection, competition, and welfare in the context of the market for privatized Medicare plans, called Medicare Advantage (MA). Using data on the advertising expenditures of MA plans in local advertising markets, individual-level and county-level MA enrollment, and characteristics of plans and markets, we first document a large difference in an insurance company's potential profits from healthy vs. unhealthy individuals. We also provide descriptive evidence that an insurer's advertising expenditure is larger in a local market where profits from enrolling healthy individuals are greater. We then develop and estimate an equilibrium model of the MA market, which incorporates strategic advertising by insurers. In the model, insurers advertise not only to increase the number of enrollees, but also to attract a larger share of healthy enrollees. Parameter estimates show that advertising has positive effects on overall demand, but a much larger effect on the demand of the healthy. Compared to a counterfactual market where advertising is banned altogether, we find that advertising accounts for 15% of the selection of healthier individuals into Medicare Advantage. We then study the impact of risk adjustment policies, which provide payments to insurers depending on their enrollee characteristics. We find that if the government switches from an existing, imperfect risk-adjusted scheme to a perfectly risk-adjusted scheme, insurers' gain from risk selection decreases, leading to a large decrease in advertising.

*We are grateful to Hanming Fang, Katja Seim, Bob Town, and Ken Wolpin for their guidance and encouragement. We also thank Mike Abito, Jason Allen, Ulrich Doraszelski, Michaela Draganska, Mark Duggan, Camilo Garcio-Jimeno, Daniel Gottlieb, Joe Harrington, SangMok Lee, Pierre-Thomas Leger, Dan Sacks, Andrew Shepherd, Michael Sinkinson, Amanda Starc, Jan Tilly, Petra Todd and seminar participants at Penn and Wharton IO lunch for valuable comments. Any remaining errors are ours. We gratefully acknowledge funding support from the Wharton Risk Center Russell Ackoff Fellowship. Kathleen Nosal kindly shared Medicare Compare Database for this paper.

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1 Introduction

Medicare provides health insurance for the majority of elderly Americans. Although traditional fee-for-service Medicare is public insurance provided by the government, many Medicare beneficiaries opt out of traditional Medicare to receive coverage from Medicare Advantage (MA) plans offered by private insurance companies. A main factor that differentiates MA plans from traditional Medicare is the provision of additional services at the cost of a restricted provider network. In 2011, about 25% of Medicare beneficiaries enrolled in MA. An MA plan receives a capitation payment from the government for its enrollee and then bears the health care costs incurred by the enrollee. The capitation payment accounts for most of the plans' revenues, even though MA plans often charge a premium.

A potential problem of MA is that private insurers have incentives to selectively enroll low-cost, healthy individuals (or "risk-select") due to an imperfect risk adjustment of capitation payments. Table 1 illustrates the presence of strong incentives for risk selection by private insurers, and the incentives are observed not only in Los Angeles but also in other regions throughout the nation. Given that regulations prohibit an MA plan from charging different premiums to individuals with different health risks, the opportunity to increase profits by enrolling healthier individuals provides insurers incentives to risk-select. Moreover, there is regional variation in the amounts of over-payment for the healthy, which creates incentives for MA plans to risk-select more intensively in regions with these higher over-payments. Indeed, previous research on MA finds that MA enrollees are healthier than traditional Medicare enrollees.[1] Although preference heterogeneity between healthy and unhealthy individuals for MA plans can partly account for the observed selection patterns, incentives for risk selection, as illustrated by Table 1, are strong.

Table 1: Capitation Payment and Health Expenditure by Health Status in Los Angeles County

	Self-reported Health Status				
	Excellent	Very Good	Good	Fair	Poor
Monthly Capitation Payment ($)	601.0	619.5	646.6	708.0	796.3
Monthly Health Expenditure ($)	266.0	347.8	575.4	923.7	2029.4
Monthly Over-payment ($)	335.0	271.3	71.2	-215.7	-1233.1

Note: Over-payment = Capitation payment - Health Expenditure.

Source: Medicare Current Beneficiary Survey 2000–2003

The main goal of this paper is to empirically study incentives for private insurers to use

[1] For examples, see Langwell and Hadley (1989); Mello et al. (2003); Batata (2004).

advertising as a means of risk selection and the impacts of advertising on the MA market. Previous work on risk selection views advertising as one of the central tools of risk selection (Van de Ven and Ellis 2000; Brown et al. 2012). MA plans might target advertising to healthy beneficiaries, for example, through its content (Neuman et al. 1998; Mehrotra et al. 2006). Moreover, advertising can be targeted to regions having greater over-payments for the healthy. When private insurers can risk-select with advertising, the effects will not be limited to MA enrollees and insurers, but the government's budget will also be affected through over-payments for the healthy. Despite the potential importance of advertising in MA, however, there is no existing quantitative analysis on the effects of advertising on risk selection or its effects on health insurance markets in general.

In order to understand the role of advertising, we develop and estimate an equilibrium model of the MA market, which incorporates strategic advertising by insurers. On the demand side of the model, consumers make a discrete choice to enroll with one of the available MA insurers or to select traditional Medicare. We assume advertising affects a beneficiary's indirect utilities, thus capturing persuasive, prestige and signaling effects of advertising. We capture the effect of advertising on risk selection with its heterogeneous effects on demand, depending on an individual's health status. Customer preferences for a plan also depend on its other characteristics such as premiums and coverage benefits. On the supply side, insurers simultaneously choose premiums and levels of advertising to maximize profits. A firm's revenue from an enrollee equals the sum of the premium and capitation payment for the enrollee, while its cost of insuring an enrollee depends on plan characteristics and the enrollee's health risk. Thus the optimal pricing and advertising of a plan takes into account the effects of these choices on the plan's composition of health risks.

Our empirical analysis relies on data from a variety of sources. First, we use data on advertising expenditures by health insurers in the 100 largest local advertising markets for the period 2000–2003 from AdSpender Database of Kantar Media, a leading market research firm.[2] Second, we use data on individual MA insurer choices, together with information on the respondents' demographic and health statuses. Third, we use data sets published by the Center for Medicare and Medicaid Services, which have information on the number of enrollees and plan benefit characteristics for each plan in each county in each year and capitation payments in each county in each year. The data show the potential importance of advertising in relation to risk selection: There is a large variation in advertising expenditures across local markets, and advertising efforts by insurance companies are concentrated in markets with higher margins from enrolling healthier individuals. Within a market, moreover,

[2] A local advertising market consists of a major city and its surrounding counties, and the 100 largest markets cover more than 80% of the total U.S. population.

healthier individuals are more likely to enroll with MA insurers that use more advertising.

We estimate the demand and supply side of the model in two steps, using generalized method of moments. For estimation of the demand model in the first step, we allow for time-invariant plan fixed effects and use instrumental variables to account for the endogeneity of premiums and advertising stemming from (time-varying) unobserved plan heterogeneity. In the second step, the supply model is estimated using the estimated demand model and optimality conditions for observed pricing and advertising choices by insurers. In the supply model, we account for the possibility that insurers choose zero advertising, which is frequently observed in the data. Parameter estimates show that advertising has a positive effect on overall demand, but a much larger effect on healthier consumers.

With the estimated model, we investigate the effects of advertising on the MA market and evaluate the effects of a policy that adjusts capitation payments based on an individual's health risks. In order to investigate the effect of advertising on the MA market, we simulate the model in an environment in which advertising is banned. The ban decreases overall MA enrollment by 4% and enrollment for MA plans with above-average advertising spending by 9%. Despite the lower demand without advertising, we find that insurers lower their premiums by very little, which results from the fact that MA enrollees become less healthy on average without advertising, raising the MA insurers' cost. The absence of advertising decreases the difference in the expected health expenditures of enrollees in traditional Medicare and MA by 15%, which reduces the average excess capitation payment per MA enrollee by 4%. This finding implies that risk selection with advertising accounts for 15% of the selection of healthier individuals into MA.

We also investigate the effects of a policy that reduces the incentive for risk selection. We consider a perfectly risk-adjusted capitation payment so that the difference between an enrollee's capitation payment and expected health expenditure is the same for any individual. We find that the risk adjustment policy has large effects on the equilibrium. Monthly premiums increase from \$30.1 to \$51.1; advertising expenditures decrease by 30%; and overall MA enrollment rates decrease by 9%. Because the risk adjustment policy reduces capitation payments for healthy enrollees, insurers compensate for the decrease in revenues by increasing premiums. Moreover, insurers reduce advertising because insuring the healthy is now less profitable. These findings highlight a strong link between risk selection and advertising.

This paper contributes to a large body of literature empirically investigating adverse selection and risk selection in insurance markets. Previous research finds that an individual's heterogeneous characteristics, such as risk, risk preference, income, and cognitive ability, are important determinants of selection patterns in insurance markets.[3] More recently, re-

[3]For examples, see Chiappori and Salanie (2000) for automobile insurance, Finkelstein and McGarry

searchers empirically investigated the possibility that the insurer affects consumer selection in different health insurance market settings. Bauhoff (2012) studies risk selection in a German health insurance market by looking at how insurers respond differently to insurance applications from regions having different profitabilities. Brown et al. (2012) provide descriptive evidence that insurers engage in risk selection in MA, using the introduction of sophisticated risk adjustment of capitation payments to MA plans. Kuziemko et al. (2013) study risk selection among private Medicaid managed-care insurers in Texas and provide evidence that the insurers risk-select more profitable individuals. Although the occurrences of risk selection are well documented in the related works, there is still little research on its channels. This paper adds to this literature by investigating the role of advertising on risk selection.

Our focus on an insurance company's behavior in insurance markets is related to a new and growing body of literature studying demand and competition in insurance markets. For example, Lustig (2011) studies adverse selection and imperfect competition in MA with an equilibrium model that endogenizes a firm's choice of premium and plan generosity by creating an index of generosity. Starc (2012) investigates the impact of adverse selection on an insurer's pricing and consumer welfare in an imperfectly competitive market (Medicare supplement insurance).[4] This paper adds to this literature by examining how advertising, which is a less explored and less regulated channel relative to competition on pricing and coverage, affects risk selection and competition.

Lastly, this paper is also related to the literature on advertising. Many empirical papers in the literature study the channels through which advertising influences consumer demand–i.e., whether advertising gives information about a product or affects utility from the product.[5] More recently, researchers have studied the effects of advertising in an equilibrium framework for different markets. Goeree (2008) studies advertising in the personal computer market in the U.S., and Gordon and Hartmann (2013) study advertising in a presidential election in the U.S. A paper that is closely related to ours is Hastings et al. (2013), who also study advertising in a privatized government program (the privatized social security market in Mexico). An important difference between this paper and the related works on advertising is that advertising in MA affects not only consumers and insurers but also the government. If MA insurers can risk-select with advertising, the enrollment decisions made by healthy individuals will directly affect government expenditures because the government over-pays for the insurance of these individuals.

(2006) for long-term care insurance, and Fang et al. (2008) for Medicare supplement insurance.

[4] For other works in this literature, see Bundorf et al. (2012); Carlin and Town (2007); Cohen and Einav (2007); Dafny and Dranove (2008); Einav et al. (2010a,b); Nosal (2012); Town and Liu (2003).

[5] For examples, see Ackerberg (2001, 2003); Ching and Ishihara (2012); Clark et al. (2009).

The paper is organized as follows. Section 2 describes Medicare Advantage in greater detail. Section 3 describes the data and presents results from the preliminary analysis. Section 4 outlines the model while Section 5 discusses estimation and identification of the model. Section 6 provides estimates of the model, and Section 7 describes results from counterfactual analyses. Section 8 concludes.

2 Background on Medicare Advantage

Medicare is a federal health insurance program for the elderly (people aged 65 and older) and for younger people with disabilities in the United States. Before the introduction of Medicare Part D in 2006, which provides prescription drug coverage, Medicare had three Parts: A, B, and C. Part A is free and provides coverage for inpatient care. Part B provides insurance for outpatient care. Part C is the Medicare Advantage program, previously known as Medicare + Choice until it was renamed in 2003.[6]

The traditional fee-for-service Medicare is comprised of Parts A and B, which reimburse costs of medical care utilized by a beneficiary who is covered by Parts A and B. As an alternative to traditional Medicare, a Medicare beneficiary also has the option to receive coverage from an MA plan run by a qualified private insurer. Insurers wishing to enroll Medicare beneficiaries sign contracts with the Center for Medicare and Medicaid Services (CMS) describing what coverage they will provide, and at what costs. The companies that participate in the MA program are usually health maintenance organizations (HMOs) or preferred provider organizations (PPOs), many of which have a large presence in individual or group health insurance markets, such as Blue Cross Blue Shield, Kaiser Permanente, United Healthcare, etc. They contract with the Center for Medicare and Medicaid Services on a county-year basis and compete for beneficiaries in each county where they operate.

The main attraction of MA plans for a consumer is that they usually offer more comprehensive coverage and provide benefits that are not available in traditional Medicare. For example, many MA plans offer hearing, vision, and dental benefits which are not covered by Parts A or B. Before the introduction of Part D, prescription drug coverage was available in MA plans, but not in traditional Medicare. Although a beneficiary in traditional Medicare is able to purchase Medicare supplement insurance (known as Medigap) for more comprehensive coverage than basic Medicare Parts A and B, the Medigap option is priced more expensively than a usual MA plan, many of which require no premium. Therefore, MA is a relatively cheaper option for beneficiaries who want more comprehensive coverage than

[6]Although we will focus on the period 2000–2003 for our analysis, we will refer to Medicare private plans as Medicare Advantage plans instead of Medicare + Choice plans.

traditional Medicare offers. In return for greater benefits, however, MA plans usually have restrictions on provider networks. Moreover, MA enrollees often need a referral to receive care from specialists. In contrast, an individual in traditional Medicare can see any provider that accepts Medicare payments.

Previous works on MA find that healthier individuals are systematically more likely to enroll in a MA plan.[7] The selection pattern may result from preference heterogeneity between healthy and unhealthy individuals for MA plans. For example, unhealthy individuals may dislike certain aspects of MA plans such as restricted provider networks and referral requirements. However, it is also possible that insurers' risk-selection reinforces the direction of consumer selection. Indeed, incentives for MA plans to risk-select are strong. By regulation, MA insurers must charge the same premium for individuals with different health statuses in a county. More importantly, capitation payments from the government do not fully account for variation in health expenditures across individuals. Until the year 2000, the CMS paid capitation payments equal to 95% of the expected costs of treating a beneficiary within traditional Medicare, and adjustments to payments were made based only on an enrollee's age, gender, welfare status, institutional status, and location. However, these adjustments, based solely on demographic information, were found to account for only about 1% of an enrollee's expected health costs (Pope et al. 2004). During the period of 2000–2003, which is a focus of this paper, the CMS made 10% of capitation payments depend on inpatient claims data using the PIP-DCG risk adjustment model, but the fraction of variations in expected health costs by the newer system remained around 1.5% (Brown et al. 2012).[8]

3 Data and Preliminary Analysis

3.1 Data

This paper combines data from multiple sources. We use the Medicare Current Beneficiary Survey (MCBS) for the years 2000–2003 for individual-level information on MA enrollment and demographic characteristics, including health status. Our data on advertising by health insurers in local advertising markets for the years 2000–2003 were retrieved from the Ad-Spender Database of Kantar Media, a leading market research firm. Market share data for the years 2000–2003 are taken from the CMS State-County-Plan (SCP) files, and in-

[7]For example, see Langwell and Hadley (1989); Mello et al. (2003); Batata (2004).

[8]From the year 2004, a more sophisticated risk adjustment model is implemented. However, Brown et al. (2012) find that MA insurers were still able to selectively enroll more profitable individuals because even the new model did not perfectly account for variation in health expenditures across individuals. The reason that we focus on the period 2000–2003 is discussed later when we introduce our data.

surers' plan characteristics are taken from the Medicare Compare databases for the years 2000–2003.[9]

The reason we study MA for the years 2000–2003 is because the MCBS does not provide information on an individual's choice of MA insurer from 2006 onward. We also avoid using data right before 2006 because Medicare Part D was introduced in that year, changing many aspects of the MA market.

3.1.1 Individual-level Data

The MCBS is a survey of a nationally representative sample of Medicare beneficiaries. This dataset provides information on a beneficiary's demographic information such as age, income, education, and location, as well as an extensive set of variables on an individual's health status: self-reported health status, difficulties in activities of daily living (ADL), difficulties in instrumental activities of daily living (IADL), and a history of diseases such as cancers, heart diseases, diabetes, etc. An important feature of this dataset is that it is linked to administrative data in Medicare, which provides information on an individual's MA insurer choice, the amount of the capitation payment paid for an MA enrollee in the sample, and the amount of Medicare claims costs for individuals in traditional Medicare.

For our analysis, we only use observations who are at least 65 years old. This means that we exclude the sample of individuals under 65 who are on Medicare solely due to disability. Although these individuals can purchase MA plans, we exclude them because the main factor that affected capitation payments for the years 2000–2003 was age and because we want to have samples of individuals who are more or less similar in terms of their capitation payments. Because beneficiaries younger than 65 years old represent a small fraction of MA enrollment (7%), we do not view this exclusion as a serious problem.

Health status An important variable from this dataset is an individual's health status. A health status can be measured in many different ways, and there are plenty of variables in the MCBS that are related to health status. Because it is very difficult to include all possible measures separately in the empirical analysis, we construct a one-dimensional continuous measure of health status. Our measure of an individual's health status is expected claims costs if an individual were to be insured by Medicare Parts A and B. To construct this measure of health status, we use information on an extensive set of observed health statuses and the realized amount of Medicare Parts A and B claims for each individual who remained in traditional Medicare. Because information on Medicare claims is available only for individuals in traditional Medicare, we have to impute expected claims costs for MA enrollees

[9] We thank Kathleen Nosal for sharing Medicare Compare data with us.

using their observed health statuses. Thus, we first estimate equations that relate Medicare claims costs to an extensive list of health characteristics using beneficiaries enrolled in traditional Medicare. Then we calculate expected claims costs not only for traditional Medicare enrollees, but also for MA enrollees.[10] A detailed discussion on constructing the health status variable is in the Appendix.

Capitation Payment For our analysis, we need to know how much an MA plan would receive when enrolling a Medicare beneficiary with certain characteristics. Unfortunately, the MCBS does not provide such information. Instead, it contains information on how much an MA plan received for a Medicare beneficiary enrolled in MA. In order to calculate a capitation payment amount for an enrollee, we exploit the fact that capitation payments were mostly based on the simple demographic factors for the years 2000–2003, as described in the previous section.[11] First, we regress an actual capitation payment for an MA enrollee in the MCBS on the enrollee's demographic characteristics that are used in the calculation of actual capitation payments. With coefficient estimates from the regression, we calculate a capitation payment for any Medicare beneficiary. Because capitation payments depend only on exogenous demographic characteristics, selection bias is not a concern here even though the regression is run with data on MA enrollees only. The coefficient estimates in the regression are reported in Table 3. The results show that the variables included in the regression explain a large part of variation in capitation payments, with R-squared of 0.822. The estimates are used to calculate a capitation payment amount for all Medicare beneficiaries including those who chose traditional Medicare.

3.1.2 Advertising Data

AdSpender contains information on the annual advertising expenditures and quantities of health insurers in different media such as TV, newspaper, and radio in the 100 largest local advertising markets in the U.S. A local advertising market consists of a major city and its surrounding counties, and its size is comparable to that of a Metropolitan Statistical Area (MSA).[12] Advertising quantity is defined as the number of times an advertisement appeared

[10] An implicit assumption here is that traditional Medicare and MA enrollees do not differ in unobserved health status. Given the extensive list of variables on health status used in imputation, however, it is reasonable to assume that we can capture most of the meaningful differences in health status.

[11] As explained in the previous section on MA, 10% of capitation payments depended on inpatient claims data for the years 2000–2003. For this version of the paper, we ignore the dependence of capitation payments on the data, which only accounted for 0.5% of health expenditures Brown et al. (2012). Given the small role of inpatient data in the calculation of capitation payments, we do not view the omission as a serious problem.

[12] In the advertising industry, this local market is usually referred to as a Designated Media Market, which is defined by Nielsen company.

in a medium in a given period, and this information is only available for TV and newspapers. AdSpender categorizes advertising across product types whenever specific product information can be detected in an advertisement, which allows us to isolate advertising expenditures for an insurer's MA plan in some instances. For example, some expenditures are reported in detail (e.g. Humana Gold plan, which is an MA plan offered by Humana Insurance Company), while others are reported more generally (e.g., Blue Cross Blue Shield health insurance in general). An advertisement falls into the latter category when it does not mention product names, or when it is for an insurer itself (not for its specific products).

In constructing a measure of advertising levels for MA plans, we excluded advertising expenditures specific to insurance products that are not MA plans. Whenever information on a product is available in the data, for example, we can tell whether the product was sold in individual or group markets for individuals not on Medicare. In the end, we use advertising expenditures for MA plans and general advertising expenditures. Because the latter is likely to be meant not only for the Medicare population but also for the non-Medicare population, we make adjustments for expenditures for general advertisements, while we do not make any changes to advertising expenditures for MA plans. To be more precise, we denote ad^{ma}_{jmt} and ad^{g}_{jmt} as a firm j's MA-specific and general advertising expenditures in a local advertising market m in year t, respectively. Our final measure of advertising expenditures for firm j's MA plans in market m in year t, ad_{jmt}, is that:

$$ad_{jmt} = ad^{ma}_{jmt} + \psi_{mt} ad^{g}_{jmt}$$

where $\psi_{mt} \in [0, 1]$ is a number we use to adjust ad^{g}_{jmt}. An important issue here is the choice of ψ_{mt}. For example, if $\psi_{mt} = 1$, the total advertising spending for MA will simply be the sum of the two kinds of advertising expenditures, which may overstate "true" MA advertising spending. For our analysis, we use ψ_{mt} equal to the fraction of the population that is at least 65 years old in each advertising market. Although the choice of ψ_{mt} is not likely to lead to a perfect measure of advertising expenditures for MA, the choice of ψ_{mt} will be a reasonable proxy for the relative importance of MA business for a firm operating in a local advertising market.[13]

In our analysis, we do not distinguish between an insurer's advertising expenditures in different media.[14] Instead, we use an insurer's total advertising expenditure in a local

[13] We plan to conduct robustness checks for the choice of ψ_{mt}.

[14] We make this choice for two reasons. The first reason is that advertising in different media does not have very distinctive effects on demand in our preliminary analysis. The second reason is that because we endogenize advertising choices in the model, and because we simulate advertising equilibrium in our counterfactual analysis, we did not want to add multiple advertising variables for which we would need to find new equilibria.

advertising market by summing the insurer's advertising expenditures across all media in the market. In analysis, we also use an insurer's total advertising quantity. Because information on advertising quantity is available only for TV and newspaper advertising, and because a unit of TV advertising is very different from a unit of newspaper advertising, we measure an insurer's advertising quantity in terms of TV-advertising-equivalent quantity. We construct this variable by dividing an insurer's total advertising expenditures in a local advertising market by the average cost of a unit of TV advertising in the market.

3.1.3 Plan-level Data

The Medicare Compare Database is released each year to inform Medicare beneficiaries which private insurers are operating in their county, what plans they offer, and what benefits and costs are associated with each plan. We take a variety of plan benefit characteristics from the data such as premiums, dental coverage, vision coverage, brand and generic prescription drug coverage, and the copayments associated with prescription drugs, primary care doctor visits and specialist visits, emergency room visits, skilled nursing facility stays, and inpatient hospital stays. In addition to information about plan benefits, the data also provide information from report cards on MA plan quality.[15] We use four measures of plan quality: ease of getting referral to specialists, overall rating of health plan, overall rating of health care received, and how well doctors communicate.

The CMS State-County-Plan (SCP) files provide the number of Medicare beneficiaries, number of enrollees of each MA insurer, and average capitation payments in each county-year. A problem with this dataset is that although many insurers offer multiple plans in the same county, the aggregate enrollment information is at the insurer-county-year level, not at the plan-insurer-county-year level. One way to deal with this issue is by taking the average of characteristics of plans offered by an insurer as representative characteristics of the insurer; and another approach is to take the base plan of each MA insurer as a representative plan because the base plan is usually the most popular.[16] [17] For the current version of this paper,

[15]Dafny and Dranove (2008) find that the report cards on MA plan quality had an impact on demand for MA plans.

[16]Previous research on MA also faced the same issue and had to deal with the issue in one of these ways. For examples, see Hall (2007); Nosal (2012).

[17]Another approach taken previously by Lustig (2011) is to use the individual-level data, MCBS. This dataset contains beneficiaries' answers to questions about characteristics of MA plans they chose such as premium paid, whether it provides vision, hearing, prescription drug coverage, etc. Using this information, Lustig (2011) was able to match plans chosen by individuals in the MCBS with a specific plan. In the current version of this paper, we do not take this approach for two reasons. First, information on an individual's choice of a specific plan is not the most important information for us given our focus on an individual's choice of an MA insurer. Second, the approach requires extensive data work because we have to compare the characteristics of an individual's plan to the characteristics of each plan offered by an insurer to match

we take the first approach, and, as a result, each MA insurer will have only one representative plan available in each county in analysis.

3.2 Preliminary Analysis

In this section, we provide summary statistics from the data and descriptive evidence on how advertising relates to risk selection. Table 4 displays characteristics of counties depending on total advertising spending in a local advertising market to which a county belongs. Although there are plenty of counties having no advertising spending, these counties are small in population. There is also a strong correlation between advertising and other county-level characteristics. Counties with larger advertising expenditures tend to have a larger fraction of Medicare beneficiaries in MA, higher capitation payments, higher health care costs in terms of traditional Medicare reimbursement rates, and more MA insurers.

Table 5 shows the presence of strong incentives for risk selection in MA. A common pattern observed in this table is that monthly capitation payments do not account for the large variation in health expenditures across individuals having different health statuses. MA insurers are paid capitation payments greater than necessary to cover the health expenditures of relatively healthy individuals whereas capitation payments for relatively unhealthy individuals are not sufficient to cover their health expenditures. As a result, MA insurers would have very strong incentives to selectively enroll healthier individuals in any county. Moreover, there is regional variation in incentives for risk selection. In counties belonging to local advertising markets with relatively large advertising spending, enrolling healthy individuals is more profitable, and enrolling unhealthy individuals results in a larger loss.[18]

In order to investigate incentives for risk selection and their regional variation more precisely, we run the following regression with the individual-level data:

$$Overpayment_i = \beta_1 rh_i + \beta_2 rh_i \times cap_{ct} + \beta_3 cap_{ct} + X_i\gamma + \epsilon_i$$

$Overpayment_i$ is the difference between in individual i's capitation payment and health status (measured in terms of expected traditional Medicare claims costs), which are calculated with the individual-level data; rh_i is individual i's relative health status, which is defined as a ratio of individual i's health status to the average Medicare claims cost in county c where

an individual with a specific plan. However, we plan on conducting robustness checks with this approach later when revising the paper.

[18] The regional variation results from the fact that the average and variance of health expenditures are positively correlated. In a region where health care is more expensive, the average health expenditure is higher. At the same time, the variance of health expenditures across individuals is also greater in the region because it is usually the health expenditures of unhealthy individuals that increase disproportionately more in a more expensive region.

individual i resides in year t; cap_{ct} is the average capitation payment in county c in year t; and X_i is a vector of other controls that determine the capitation payment for individual i such as age, Medicaid status, and institutional status. Regression results are presented in Table 6. Because the minimum county-level average capitation payment is larger than 200, $\hat{\beta}_1 + \hat{\beta}_2 cap_{ct} < 0$ in any county in any year. This means that more over-payments will be made in regions having healthier individuals (lower rh_i). Moreover, $\hat{\beta}_2 rh_i + \hat{\beta}_3 > 0$ for $rh_i < 0.97$, and the median and mean of rh_i are 0.6 and 0.89, respectively. This means that over-payments for relatively healthy individuals are greater in regions with higher average capitation payments. These results are summarized in Figure 1, which is based on an individual of age 75 who is not eligible for Medicaid and not living in a nursing home. The plots show that MA plans can increase profit by enrolling healthier individuals and that risk selection is more profitable in regions with higher average capitation payments.

Now given that insurers have more incentives for risk selection in regions with higher capitation payments, we investigate how an insurer's advertising in a local adverting market is related to regional variation in capitation payments with the following regressions:

$$\begin{aligned} ad_{jmt} &= \beta cap_{mt} + X_{mt}\gamma + \delta_j + \epsilon_{jmt} \\ ad_{jmt} &= \beta cap_{mt} + X_{mt}\gamma + \xi_{jm} + \epsilon_{jmt} \end{aligned}$$

The two regressions are different only with respect to fixed effects. In the first specification, δ_j denotes insurer fixed effects which are invariant over local advertising markets (m). In the second specification, ξ_{jm} denotes insurer-advertising market fixed effects. ad_{jmt} is either an advertising quantity or expenditure by insurer j in local advertising market m in year t, depending on specification.[19] cap_{mt} is the weighted average of cap_{ct} (the average capitation payment in county c in year t) across counties in local advertising market m, with the population of each county as a weight. X_{mt} is a vector of other control variables such as the population of market m, local TV advertising cost and number of competing insurers in an advertising market. The results are reported in Table 7. For any specification, the results indicate that more advertising is done in local advertising markets with higher average capitation payments, where over-payments for healthy enrollees are greater. That is, MA insurers' amounts of advertising respond to regional variation in the profitability of risk selection.

Lastly, Table 8 shows that individuals with different health statuses are likely to be enrolled with different insurers. MA plans in general tend to have healthier Medicare ben-

[19] After all, we run four different regressions. Each equation is estimated with each of the two dependent variables.

eficiaries than traditional Medicare, which is consistent with previous findings on selection into MA. Among MA insurers, moreover, firms with more advertising tend to have healthier enrollees.

4 Model

As discussed in a previous section, MA insurers contract with CMS for each county (c) in each year (t). As a result, consumers in different counties face different choice sets. However, each advertising decision is typically made on the basis of a local advertising market (m), which contains several counties. Thus we assume individuals in different c but in the same m are exposed to the same advertising level by the same firm. If county c is included in ad market m, we denote $c \in m$.

4.1 Demand

Consider a consumer i, living in a county $c\,(\in m)$ in year t. Consumer i chooses to enroll with one of the available MA insurers in each c and t or in traditional Medicare. We assume that consumer i, living in a county c in year t, obtains indirect utility u_{ijct} from insurer j as follows:

$$u_{ijct} = g(ad_{jmt}, rh_i; \phi) + p_{jct}\alpha_i + x_{jct}\beta_i + \overline{\xi_{jc}} + \Delta\xi_{jct} + \epsilon_{ijct}$$

where

$$\begin{aligned} g(ad_{jmt}, rh_i; \phi) &= (\phi_0 + \phi_1 \log(rh_i)) \times \log(1 + \phi_2 ad_{jmt}); \\ \alpha_i &= \alpha_0 + \alpha_1 \log(rh_i); \\ \beta_i &= \beta_0 + \beta_1 \log(rh_i). \end{aligned}$$

Each insurer has observable characteristics (ad_{jmt}, p_{jct}, and x_{jct}), insurer-county fixed effect ($\overline{\xi_{jc}}$), and an unobservable characteristic ($\Delta\xi_{jct}$). First, ad_{jmt} denotes insurer j's advertising quantity in advertising market m in year t. The effect of advertising on indirect utility u_{ijct} is captured by $g(ad_{jmt}, rh_i; \phi)$, which depends on individual i's relative health status (rh_i).[20] Parameter ϕ_0 reflects the effects of advertising that are independent of an individual's health status. The effects of advertising on risk selection are captured by its

[20] rh_i is defined as a ratio of individual i's health status (in terms of expected Medicare claims cost) to the average Medicare expenditure in county c where individual i resides in year t. This definition of rh_i is used in the previous section for preliminary analyses.

heterogeneous effects on individuals with different rh_i (ϕ_1). We assume that the effects of advertising diminish in its quantity by assuming that ad_{jt} enters $g(\cdot)$ in logarithm. Parameter ϕ_2 determines the curvature of function $g(\cdot)$.

With this specification of u_{ijct}, we assume that advertising affects indirect utility from an insurer, which is consistent with the persuasive, prestige and signaling effects of advertising. The persuasive and prestige effects of advertising would directly affect utility from an insurer, for example, by creating a certain positive image associated with the insurer (Stigler and Becker 1977; Becker and Murphy 1993). Indeed, many advertisements for MA show images of seniors living healthy lives: engaging in physically demanding activities like running and golfing (Neuman et al. 1998; Mehrotra et al. 2006). These advertisements may create a positive image associated with an insurer and lead to a higher utility level from a plan of that insurer. The signaling effects of advertising will affect demand for an insurer through expected utility by giving a signal about the (unobservable) quality of the insurer (Nelson 1974; Milgrom and Roberts 1986). Because indirect utility u_{ijct} is supposed to capture expected utility from an insurer, $g(ad_{jmt}, rh_i; \phi)$ will contain both effects of advertising. Another possible effect of advertising we do not exactly model is the provision of information about the existence of a product, which is likely to affect an individual's consideration set. If advertising in MA indeed has such effects, they will be captured as an increase in $g(ad_{jmt}, rh_i; \phi)$ because we do not model the effects of advertising on an individual's consideration set.[21]

p_{jct} denotes the premium of plan jct which a consumer pays in addition to the Medicare Part B premium.[22] The effect of p_{jct} on utility is also potentially heterogeneous depending on an individual's health status. This is captured by parameter α_1. x_{jct} describes plan jct's characteristics other than ad_{jmt} and p_{jct}. For example, x_{jct} includes copayments for a variety of medical services such as inpatient care and outpatient doctor visits and variables describing drug coverage, vision coverage, dental coverage, etc. x_{jct} also includes quality measures of insurers taken from report cards on MA plan quality. The quality measures included in x_{jct} are ease of getting a referral, overall rating of health care received through a

[21] Effects of advertising on a consumer's consideration set would be especially important in an environment where the number of available insurers is so large that consumers cannot easily know about available options. In the MA market, however, the number of available insurers is limited for many individuals. About 40% of Medicare beneficiaries have at most two insurers available in their county of residence; and about 70% of Medicare beneficiaries have at most four insurers available in their county of residence. Thus, although the informative effects of advertising can be still important in the MA market, the effects are not likely to be as important as in markets with a large number of available products.

[22] When enrolling in a MA plan, an individual must pay the Medicare Part B premium as well as the premium charged by the plan. Here I did not include Medicare Part B premium in p_{jct} because almost all Medicare beneficiaries, who remain in traditional Medicare, enroll in Medicare Part B and pay the Medicare Part B premium.

MA plan, and how well doctors in a MA plan communicate.[23] With these quality measures, we can control for an insurer's characteristics that would be usually considered unobserved. The effects of x_{jct} are potentially heterogeneous with parameter β_1 capturing the differential effects of x_{jct} on individuals having different health statuses.[24]

$\overline{\xi_{jc}}$ denotes insurer-county fixed effects that capture time-invariant unobserved characteristics of insurer j in county c such as size and quality of the insurer's networks in a region. An individual's utility also depends on aspects of an insurer that are unobserved by researchers but observed by consumers and insurers. $\Delta\xi_{jct}$ is a time-specific deviation from $\overline{\xi_{jc}}$. $\Delta\xi_{jct}$ captures time-varying unobserved characteristics and/or shocks to demand for this insurer. We assume that $\Delta\xi_{jct}$ is known by consumers and insurers when they make decisions. Lastly, ϵ_{ijct} is idiosyncratic preference shock, which we assume is drawn from Type I extreme value distribution and i.i.d across individuals, insurers, counties and years.

In the model, the outside option is to enroll in traditional Medicare, from which a consumer receives utility of u_{i0ct}:

$$u_{i0ct} = z_i\lambda + \epsilon_{i0ct}.$$

z_i is a vector of an individual's characteristics including relative health status (rh_i), age, Medicaid status, and whether the individual receives insurance benefits from an (former) employer. These individual characteristics in u_{i0ct} will control for the possibility of different values of the outside option relative to MA, depending on individual characteristics. For example, Medicaid-eligible individuals will receive more comprehensive coverage in traditional Medicare without having to pay an additional premium. Those who receive insurance benefits from employers will also have a different value of the outside option compared to individuals only with basic Medicare Parts A and B coverage. Moreover, many Medicare beneficiaries in traditional Medicare purchase Medicare supplement insurance (so-called Medigap). Medigap is used in conjunction with traditional Medicare and covers out-of-pocket expenditure risks of individuals in traditional Medicare.[25] Because we do not allow for an additional choice of purchasing Medigap in the model, the utility from the possibility of purchasing Medigap is included in u_{ioct}. Previous research on Medigap finds that selection into Medigap depends on an individual's characteristics such as health status (Fang et al. 2008). Then coefficient λ will also capture heterogeneous preference for Medigap depending on z_i. Moreover, it is possible that individuals have different preferences for MA. For example, unhealthier individuals may dislike common aspects of MA plans such as restricted provider networks and

[23]A detailed list of the variables used in analysis is reported in the Appendix.

[24]In order to reduce the number of parameters to be estimated, we do not interact every variable in x_{jct} with health status. We select which variables to interact with health status based on the results of the preliminary analysis. A complete list of variables interacted with health status is reported in the Appendix.

[25]About 25% of Medicare beneficiaries purchase a Medigap plan.

referral requirements for specialized treatments. In this case, parameter λ will also capture heterogeneous preferences for MA.

With the functional-form assumption on ϵ_{ijct}, we can analytically calculate the probability for an individual i with characteristics z to enroll plan jct. By defining $u_{jct}(z_i) \equiv u_{ijct} - \epsilon_{ijct}$, we can write the choice probability for plan jct as follows:

$$q_{jct}(z) = \frac{\exp\left(u_{jct}(z)\right)}{\exp(u_{0ct}(z)) + \sum_{k \in J_{ct}} \exp\left(u_{kct}(z)\right)} \tag{1}$$

Then aggregate market share for a firm jct is

$$Q_{jct} = \int_z q_{jct}(z) dF_{ct}(z) \tag{2}$$

where $F_{ct}(z)$ is the distribution of individual characteristics z in county c and year t.

4.2 Supply

We assume that insurers play a simultaneous game in choosing optimal pricing and advertising in each advertising market. In the model, a pricing decision is made for each county (c) in each year (t), and an advertising decision is made for each advertising market (m) in each year (t).

When insuring an individual with health status h (a nominal health expenditure, not relative health rh) with plan characteristics x_{jct} and market characteristics w_{ct}, insurer jct expects to incur a marginal cost $c_{jct}(h)$ as follows:

$$c_{jct}(h) = x_{jct}\gamma_1 + w_{ct}\gamma_2 + h\gamma_3 + \psi_j + \eta_{jct}. \tag{3}$$

x_{jct} is a vector of plan characteristics which are included in the utility specification of a consumer such as drug coverage, copayment amounts for a variety of services, etc. w_{ct} includes county characteristics that can potentially influence the cost of providing insurance, including the number of hospitals, skilled nursing facilities and physicians in a county. For example, insurers may be able to negotiate lower payments with providers in markets having a large number of physicians and hospitals (Ho 2009). Importantly, the marginal cost of insuring a consumer depends on the consumer's health status h, and this aspect of $c_{jct}(h)$ creates incentives for risk selection. ψ_j is a firm fixed effect that capture different administrative costs and different ways of delivering health care at the firm level (e.g., Aetna, Blue Cross Blue Shield, Secure Horizon, etc.). Lastly, η_{jct} is a firm-county-year-specific shock to marginal costs that is constant across individuals with different h. We assume that η_{jct} is observed by all insurers making pricing and advertising decisions in a market.

Insurer j's profit from a county c in year t, excluding advertising costs, is given by:

$$\pi_{jct} = M_{ct} \int_z (p_{jct} + cap_{ct}(z) - c_{jct}(h)) q_{jct}(z) dF_{ct}(z).$$

M_{ct} is the population of those who are at least 65 years old in county c in year t, which is the market size; p_{jct} is the premium charged by insurer j in county c in year t; $cap_{ct}(z)$ is a capitation payment that depends on county, year, age, gender, Medicaid status and institutional status; and $q_{jct}(z)$ is demand for insurer j by an individual having characteristics z in (1).

Because each insurer makes an advertising decision for each advertising market, we need to consider an insurer's profit in an advertising market in order to analyze its advertising choice. An insurer j's profit in advertising market m and year t is:

$$\pi_{jmt} = \sum_{c \in m} \pi_{jct} - mc_{jmt} ad_{jmt}$$

where mc_{jmt} is constant marginal cost per unit of advertising. We assume that

$$mc_{jmt} = \exp\left(x^{ad}_{jmt} \gamma_{ad} + \zeta_{jmt}\right).$$

x^{ad}_{jmt} includes the costs of TV advertising in media market m in year t, year dummies, and dummy variables for large firms. We included eight dummy variables for each of the eight largest firms. These dummy variables will capture different resources constraints faced by different firms.[26] [27] ζ_{jmt} is a shock to the marginal cost, which is also known by all insurers in a media market, but unobserved by researchers. We assume that $\zeta_{jmt} \sim N(0, \sigma^2_\zeta)$.[28]

Nash equilibrium conditions for the game for insurers are that insurers' choices maximize their profits given choices made by other insurers. For an insurer's optimal pricing condition, we have the following condition for each p_{jct}:

$$\frac{\partial \pi_{jmt}}{\partial p_{jct}} = \frac{\partial \pi_{jct}}{\partial p_{jct}} = 0. \tag{4}$$

[26] Although marginal cost of advertising is assumed to be constant, some firms using large amounts of advertising may face different advertising costs due to volume discounts. The dummy variables can capture the different discounts received by different firms having potentially different advertising amounts.

[27] Included insurers are Secure Horizon, Blue Cross Blue Shield, Kaiser Permanente, United Healthcare, Aetna, Humana, Health Net, and Cigna. Although Secure Horizon is currently part of United Healthcare, they were separate companies during the period of 2000–2003.

[28] The reason that we make a functional-form assumption for ζ will be discussed in the section for identification and estimation.

An insurer's optimal advertising conditions are:

$$\frac{\partial \pi_{jmt}}{\partial ad_{jmt}} = \sum_{c \in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}} - mc_{jmt} \begin{cases} = 0 & \text{for } ad_{jmt} > 0 \\ \leq 0 & \text{for } ad_{jmt} = 0 \end{cases}. \tag{5}$$

For the optimal advertising condition, we explicitly allow for the possibility of the corner solution, which is no advertising.[29] Because about 35% of insurer (j)-market (m)-year (t) combinations do not advertise at all, we have to explicitly allow for the possibility that insurers choose the corner solution. Condition (5) states that when an insurer spends a positive amount of advertising spending, the optimal quantity of advertising maximizes its profit, and that when an insurer does not advertise, its profit gain from a small quantity of advertising should not be greater than its cost.

5 Identification and Estimation

For the discussion of identification and estimation of the model, we define θ as a vector that contains all parameters in the model such that $\theta = (\theta^d, \theta^s)$. θ^d and θ^s are vectors of parameters that enter the demand and supply side, respectively.

5.1 Demand

Mean Utility In utility u_{ijct}, there are two kinds of parameters: θ_1^d and θ_2^d. We define θ_1^d to be parameters that enter 'mean utility' δ_{jct}, which is a part of u_{ijct} that does not depend on individual characteristics. Precisely,

$$\delta_{jct} = \phi_0 \log(1 + \phi_2 ad_{jmt}) + \alpha_0 p_{jct} + x_{jct}\beta_0 + \overline{\xi_{jc}} + \Delta\xi_{jct}. \tag{6}$$

θ_2^d is defined as parameters for interaction terms between insurer characteristics and individual characteristics. We let ϕ_2, which determines diminishing returns of advertising effects, be a part of θ_2^d. Berry et al. (1995) show that given a value for θ_2^d, there is a unique $\delta_{jct}^*(\theta_2^d)$ that solves for the system of equations given by the aggregate market share equation (2). Then parameter θ_1^d is estimated using equation 6. A well-known problem regarding identification of θ_1^d is that the unobserved characteristic ($\Delta\xi_{jct}$) and two endogenous variables in the

[29] Although premiums can be zero, we assume that even zero premium satisfies the pricing first order condition with equality. This assumption is made mainly for computational convenience when solving the model in counterfactual analysis. If an insurer chooses zero premium due to the constraint of nonnegative premium, it is possible that we overestimate the marginal cost of providing insurance for insurers having zero premium.

model (p_{jct} and ad_{jmt}) are correlated, because $\Delta\xi_{jct}$ is assumed to be known by consumers and insurers when they make decisions. This problem is a typical endogeneity problem, and then a simple ordinary least squared regression of $\delta^*_{jct}(\theta^d_2)$ on the observed variables in (6) will result in inconsistent estimates of θ^d_1.

Although the endogeneity problem causes challenges in identification, fixed effects $\overline{\xi_{jc}}$ in δ_{jct} would control for a significant part of the unobserved heterogeneity of insurers. Important characteristics that are not included in x_{jct} are an insurer's network size and quality in a local market. For example, Kaiser Permanente, which is one of the largest insurers in California, has a more extensive network in California than in other regions. As long as such characteristics do not vary much over the time period considered in this paper, they will be controlled for by $\overline{\xi_{jc}}$. Moreover, x_{jct} includes an insurer's quality measures from report cards on MA plan quality, such as ease of getting a referral, overall rating of an insurer, overall rating of health care received, and how well an insurer's physicians communicates with patients. By including these characteristics, we will be able to control for characteristics that would usually be considered unobservable.

However, it is still possible that x_{jct} cannot capture all relevant characteristics of an insurer that vary over time, which will result in the endogeneity problem. A typical approach to accounting for the endogeneity problem is to use instruments that are correlated with the endogenous variables, but not with the unobservable. We construct two sets of instruments. The first set of instruments are the averages of premiums and advertising of the same parent company in other advertising markets. The use of functions of endogenous variables in other counties as instruments is a strategy similar to Hausman (1996) and Nevo (2001). Town and Liu (2003) use similar instruments in estimating a model of demand for MA plans. The identifying assumption is that demand shock $\Delta\xi_{jct}$ is not correlated with shocks affecting the premiums of insurer j in other markets, such as demand and marginal cost shocks in the markets. A similar identifying assumption is made for advertising of the same firm in other markets. A premium in a county will be correlated with the average premiums of the same firm in other markets through, for example, common company-level components affecting premiums. The same argument also holds for advertising.

The second set of instruments are variables that affect a plan's premium and advertising choices, but do not affect utility directly. One such variable is the cost of a unit of TV advertising in a local advertising market, which affects an advertising decision, but does not affect utility directly. Other such variables are capitation payments in other counties in the same advertising market. Because capitation payments in other counties in the same advertising market will affect advertising in the advertising market, the payments in other counties can be valid instruments as long as they do not enter the utility of a consumer in a county.[30]

Resulting moment conditions employed in the estimation are:

$$E[\Delta\xi_{jct}|\Gamma] = 0. \tag{7}$$

Γ is a set of instruments that includes the aforementioned two sets of instruments as well as x_{jct}.

Preference Heterogeneity Important information for identification of parameters for preference heterogeneity θ_2^d is an individual's insurer choice from the MCBS (the individual-level data). Parameter θ_2^d will be identified by variation in the characteristics of insurers chosen by individuals having different characteristics. Identification of θ_2^d is aided by variation in insurer characteristics, not only across insurers within a region but also across regions. For example, advertising quantities vary across local advertising markets depending on how profitable risk selection is in the market, as illustrated in the previous section for preliminary analysis. Moreover, individuals in different regions will have different choice sets, and this variation in choice sets provides information on the substitution patterns of different individuals.

An important parameter in θ_2^d is the parameter that determines the heterogeneous effect of advertising depending on an individual's health status (ϕ_1), which captures the effect of advertising on risk selection. A potential concern in identifying ϕ_1 is that there may be insurer characteristics, not included in x_{jct} but correlated with ad_{jmt}, that have different effects on the demand of individuals having different health status. Given the available data, it is impossible to allow for insurer-county fixed effects $\overline{\xi_{jc}}$ that depend on an individual's health status and to control for them.[31] In order to alleviate this concern, we interact many different variables in x_{jct} with health status, including not only usual characteristics such as drug coverage and copayments but also the quality measures from report cards on MA plans and dummy variables for each of the seven largest insurers. The latter variables are highly correlated with ad_{jmt}, and their interactions with health status will limit the role of omitted insurer characteristics that can have differential effects on individuals having different health statuses. The quality measures will control for important aspects of insurers, with potential heterogeneous effect, that cannot be described by usual coverage characteristics. Moreover, an interaction between a dummy variable for a large insurer and health status will capture

[30]The second instrument using capitation payments in other counties is similar to the instruments used in Nosal (2012), who studies demand for MA plans.

[31]If there is information on an insurer's aggregate market share by different health statuses, it is possible to allow for $\overline{\xi_{jc}}$ that depends on health status.

an aspect of the insurer that may have differential effects on individuals having different health statuses.

In order to construct micro-moments for an individual's insurer choice and combine them with aggregate moments (7), we use the score of the log-likelihood function for a choice by an individual observed in the MCBS, as in Imbens and Lancaster (1994). The likelihood function for an individual's choice is:

$$L = \prod_{i,j,c,t} q_{jct}(z_i)^{d_{ijct}}$$

where z_i is a vector of characteristics of individual i in the individual-level data; and d_{ijct} is an indicator variable that equals one when individual i chooses plan jct. Then our micro-moments are

$$\frac{\partial \log(L)}{\partial \theta_2^d} = 0. \tag{8}$$

5.2 Supply

Cost of Providing Insurance Estimation of parameters of the supply side relies on the optimality conditions for pricing and advertising, presented in (4) and (12). The first order condition for optimal pricing (4) is equivalent to the following condition:

$$\begin{aligned} \frac{Q_{jct} + \int_z (p_{jct} + cap_{ct}(z)) \frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z)}{\frac{\partial Q_{jct}}{\partial p_{jct}}} &= \frac{\int_z c_{jct}(h) \frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z)}{\frac{\partial Q_{jct}}{\partial p_{jct}}} \\ &= x_{jct}\gamma_1 + w_{ct}\gamma_2 + H(q_{jct}, F_{ct})\gamma_3 + \psi_j + \eta_{jct} \end{aligned} \tag{9}$$

where $q_{jct}(z)$ and Q_{jct} are demand of an individual with characteristic z (which includes h) and aggregate demand for insurer j in county c in year t, respectively; and

$$H(q_{jct}, F_{ct}) \equiv \frac{\int_z h \frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z)}{\frac{\partial Q_{jct}}{\partial p_{jct}}}.$$

An examination of (9) reveals that its left-hand side is a function of demand side parameters and data. Because demand side parameters can be identified with only the demand model and data, the left-hand side of (9) can be treated as known. Then optimality condition (9) leads to a linear estimating equation. Because we assume that an insurer's choice of x_{jct} is exogenous to the model, and because market characteristics w_{ct} are exogenous, we have the following moment conditions:

$$E[\eta_{jct}|x_{jct}] = 0 \text{ and } E[\eta_{jct}|w_{ct}] = 0. \tag{10}$$

These assumptions will identify parameters γ_1 and γ_2.

However, we cannot have a similar condition for parameter γ_3 because $H(q_{jct}, F_{ct})$ is potentially endogenous to η_{jct}. Because an insurer's choice of p_{jct} will be directly dependent on η_{jct} in the model, and because p_{jct} will determine $q_{jct}(z)$, variable $H(q_{jct}, F_{ct})$ may be correlated with η_{jct}. This endogeneity problem necessitates an instrument that is correlated with $H(q_{jct}, F_{ct})$, but not with η_{jct}. In order to find an instrument for $H(q_{jct}, F_{ct})$, it is important to understand what $H(q_{jct}, F_{ct})$ means. By definition, $H(q_{jct}, F_{ct})$ measures the average health status of consumers switching from insurers jct to other insurers due to an increase in a premium of insurer jct. Because an individual's health status h is measured as expected claims cost for Medicare Parts A and B, an important determinant of $H(q_{jct}, F_{ct})$ is overall health care cost in county c in year t. As a result, $H(q_{jct}, F_{ct})$ must be highly correlated with county-level average Medicare claims cost FFS_{ct}, which exhibits large variation across counties. Since we control for market characteristics w_{ct} that may influence an insurer's marginal cost, it is likely that FFS_{ct} is uncorrelated with η_{jct}, which leads to the identifying assumption for γ_3 such that

$$E[\eta_{jct}|FFS_{ct}] = 0. \tag{11}$$

Advertising Cost The optimality condition for an advertising quantity (5) identifies parameter γ_{ad} in advertising marginal cost mc_{jmt}. This condition is equivalent to the following condition:

$$\zeta_{jmt} \begin{cases} = \log\left(\sum_{c\in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}}\right) - x^{ad}_{jmt}\gamma_{ad} & \text{for } ad_{jmt} > 0 \\ \geq \log\left(\sum_{c\in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}}\right) - x^{ad}_{jmt}\gamma_{ad} & \text{for } ad_{jmt} = 0 \end{cases} \tag{12}$$

As is clear in (12), the optimality condition for insurers using zero advertising results in an inequality condition, which creates a challenge in estimation and identification. We deal with this problem by assuming a functional form for the distribution for advertising cost shock ζ_{jmt} such that $\zeta_{jmt} \sim N(0, \sigma^2_\zeta)$.[32] [33] In order to set up moment conditions, we use the score of the log-likelihood function for each insurer's observed advertising quantity choice, using

[32] Goeree (2008) faces the same problem of rationalizing zero advertising by some firms in the personal computer market, and she also deals with this problem by making a functional-form assumption for the unobservable.

[33] Note that a function-form assumption is not necessary for η when estimating the parameters in the marginal cost of providing insurance because there are no inequality optimality conditions for pricing.

the first order conditions (12). The likelihood function for the advertising choice is:

$$\Gamma = \prod_{j,m,t} f_\zeta(\zeta^*_{jmt})^{\mathbf{1}[ad_{jmt}>0]} \left(1 - F_\zeta(\zeta^*_{jmt})\right)^{\mathbf{1}[ad_{jmt}=0]}$$

where $\zeta^*_{jmt} = \log\left(\sum_{c\in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}}\right) - x^{ad}_{jmt}\gamma_{ad}$, and f_ζ and F_ζ are the pdf and cdf of ζ. Then the moment conditions for advertising cost are

$$\begin{aligned} \frac{\partial \log(\Gamma)}{\partial \gamma_{ad}} &= 0 \\ \frac{\partial \log(\Gamma)}{\partial \sigma_\zeta} &= 0. \end{aligned} \tag{13}$$

An alternative approach, not taken in this paper, is to set-identify γ_{ad} using the moment inequality method as in Pakes et al. (2011), which will result in an upper and lower bound for γ_{ad}. If the moment inequality method is used, it will be straightforward to calculate a lower bound by calculating an increase in profits (excluding advertising cost) when insurers increase a unit of advertising from the amount observed in the data. Marginal cost of advertising must be greater than the calculated increase in profits because the observed advertising quantity is assumed to maximize profits. A moment for a lower bound is calculated by averaging over each insurer's lower bounds for advertising cost.

A natural way to derive an upper bound of advertising cost is to calculate the decrease in profits when insurers decrease a unit of advertising from the observed advertising choice. However, deriving the upper bound is more challenging in this model because some insurers choose zero advertising and because an advertising quantity cannot be negative. As a result, we can calculate upper bounds only for insurers that choose positive advertising quantities. Because we can only average over insurers with positive advertising for a moment for the upper bound, we will have a selection problem. However, Pakes et al. (2011) show that if a researcher assumes that ζ comes from a symmetric distribution, it is still possible to derive an upper bound.

A tradeoff between the two approaches to dealing with the inequality first order conditions is that a functional-form assumption on ζ can lead to point-identification of parameters at the cost of a stronger assumption on unobservable ζ. However, the moment inequality method is not completely free of an assumption on ζ either. For this reason, we choose to make a functional-form assumption.[34]

[34]For robustness checks, we plan to check how our results depend on different assumptions on ζ and to estimate the model with the moment inequality method.

5.3 Estimation Algorithm

The demand and supply models are estimated separately in two steps. The estimation method we use is generalized method of moments. First, we estimate the demand model using moments (7) and (8) with the nested fixed point algorithm as in Berry et al. (1995). We define $G_d(\theta^d)$ to be a vector of the moments for the demand side. Our criterion function is given by $\Psi_d(\theta^d) = G_d(\theta^d)' W G_d(\theta^d)$ where W is a weighting matrix. Our estimation routine searches for θ^d that minimizes $\Psi_d(\theta^d)$. Evaluation of $G_d(\theta^d)$ can be broken into the following steps for each choice of θ^d:

1. Given θ^d, we solve for mean utility $\delta^*(\theta^d) = \{\delta^*_{jct}(\theta^d)\}_{j,c,t}$ that satisfies the conditions for aggregate market shares (2), using the contraction mapping used in Berry et al. (1995).

2. With θ^d and $\delta^*(\theta^d)$, we calculate the demand $q_{jct}(z)$ of an individual with characteristic z using equation (1).

3. We evaluate $G_d(\theta^d)$ with $q_{jct}(z)$.

Once we estimate θ^d, the supply model is estimated using moments (10), (11), and (13).

6 Estimates

6.1 Utility

Table 9 displays estimates for the parameters of primary interest. The estimate of the parameter for the differential effects of advertising on utility is negative, which means that the effects of advertising are greater for healthier consumers because a healthier individual has lower rh_i. The total effect of advertising on an individual with relative health status rh_i is $\phi_0 + \phi_1 \log(rh_i)$. In the data, the median of $\log(rh_i)$ is -0.6, and the value of $\log(rh_i)$ is negative for a majority of individuals.[35] As a result, although the estimate for ϕ_0 is not large enough to be statistically significant, $\phi_0 + \phi_1 \log(rh_i)$ will be larger than ϕ_0 for many individuals with $\log(rh_i) < 0$. Moreover, less healthy individuals receive more utility from the outside option than healthier individuals, according to the estimates for the parameters for relative health status in the utility for the outside option. In other words, healthier individuals are more likely to choose MA than less healthy individuals even without advertising. The estimates for price coefficients indicate that individuals receive negative utility from a

[35] The distribution of rh has a long right-tail. The median of rh is 0.6, and the mean of rh is 0.9.

higher premium, and that healthier individuals are less sensitive to premium although the estimate for α_1 is not statistically significant.

Table 10 presents semi-elasticities of demand with respect to an increase of $1,000 in advertising expenditures, which measures percentage change in demand for a $1,000 increase in advertising expenditures.[36] An increase of $1,000 in advertising expenditures by an insurer increases demand by 0.063% on average. Elasticities for different health statuses show that the effects of advertising are substantially different across individuals having different health statuses. The elasticity for an individual whose rh_i is lower than the 25th-percentile of the distribution of rh_i is more than four times greater than the elasticity for an individual, whose rh_i is more than the 75th-percentile of the distribution of rh_i. Semi-elasticity of demand with respect to a premium is -0.25, which means that a dollar increase in a premium decreases demand by 0.25%. Moreover, healthier individuals' price semi-elasticity is larger in its absolute value than that of less healthy individuals.

The estimates imply that although MA plans are preferred by healthy individuals in general, advertising reinforces the direction of selection into MA. As mentioned in a previous section, unhealthy individuals may dislike the HMO aspects of MA plans such as restricted provider networks and referral requirements for specialized medical treatment. These aspects will be especially inconvenient especially for unhealthy individuals, who expect to utilize medical care intensively. In addition to the heterogeneous preferences between healthy and unhealthy individuals for MA, advertising also attracts healthier individuals into MA.

There are several mechanisms to generate the estimated heterogeneous effects of advertising on demand. First, the estimates may reflect contents of advertising designed to be more appealing to healthy individuals, as claimed by Neuman et al. (1998) and Mehrotra et al. (2006). Alternatively, insurance companies may deliberately choose which media to advertise because individuals with different characteristics may be exposed to different media to different degrees. For example, more educated individuals are more likely to read a newspaper, and insurers may target these individuals with newspaper advertising because more educated individuals tend to be healthier.[37] Another possibility is that individuals with different health statuses respond differently to the same advertising. In order for an insurer's advertising to induce an individual to enroll with the insurer, the individual must be able to purchase a plan from the insurer. In fact, many Medicare beneficiaries have difficulties with

[36] We calculate semi-elasticity instead of elasticity because zero advertising is observed for about 35% of insurers. When an advertising expenditure is zero, elasticity becomes zero. For the same reason, we calculate semi-elasticity for premiums. MA insurers often charge a premium of zero.

[37] An example of research that studies the effects of advertising in different media on individuals with different characteristics is Goeree (2008), who studies advertising in the U.S. personal computer market. We are unable to incorporate this detailed mechanism of risk selection into our analysis because of the lack of data that relate an individual's characteristics and media consumption patterns.

activities related to purchasing a plan according to the individual-level data: About 10% of Medicare beneficiaries have difficulties in using the telephone; about 20% of them have difficulties in shopping for personal items; about 15% of them have difficulties in managing money; and about 50% of them do not use the Internet. Moreover, individuals with such characteristics are more likely to be unhealthy in the data. Then individuals without the difficulties who would be induced by advertising are likely to be relatively healthy.

Estimates for other parameters in utility are reported in Table 11 and 12. Many variables that enter mean utility are statistically significant. For example, consumers prefer insurers that offer generic and brand drug coverage and drug coverage without an annual coverage limit. However, many variables that interact with health status are not statistically significant. Exceptions are the coefficients for Medicaid status and whether an individual receives health insurance benefits from a (former) employer, which determine heterogeneous utility of the outside option. As expected, individuals on Medicaid are less likely to purchase a MA plan; and individuals with employer-sponsored benefits are also less likely to purchase MA. These estimates result from the fact that having either option usually increases the value of staying in traditional Medicare. Medicaid, combined with Medicare, provides more generous coverage than traditional Medicare, without an additional premium. Moreover, employer-sponsored benefits also provide a cheap option for supplemental coverage without MA plans.

The imprecise estimates for the parameters for most interaction terms imply that many plan characteristics do not have large impacts on the insurer choice of individuals with different health statuses. This may be because variation in the data that identifies the relevant parameters comes from observed insurer choices, not plan choices, by individuals with different health statuses. Even if individuals with different health statuses select into plans with different characteristics within an insurer, an observed insurer choice cannot provide information on such selection patterns unless the characteristics of overall plans of different insurers are very different.[38] However, parameters for the effects of insurer-level characteristics, such as advertising quantities and dummy variables for large insurers, will not be affected by our focus on an individual's choice of insurer because these characteristics are constant across each insurer's plans.

6.2 Cost

Table 13 displays estimates for marginal costs of providing insurance to an enrollee whose specification is given in (3). The most important parameter here is the coefficient for health

[38]As a robustness check, we plan to consider the possibility that individuals make a choice at the plan-level, not at the insurer-level. See footnote 17 for details.

status, which is measured as expected Medicare reimbursement costs. The coefficient is very precisely estimated, and its effect is that a one-dollar increase in expected Medicare claims cost leads to an increase of $0.86 for an MA insurer. This means that the average health status of an insurer's enrollees is an important determinant of the insurer's cost of providing insurance, which will create strong incentives to risk-select healthy individuals.

The marginal cost of providing insurance also depends on other characteristics. Notably, county-level characteristics are important determinants of marginal cost. We find that marginal cost increases with population density and with the percentage of the population that lives in urban areas. It may be because counties, which are densely populated and urban, are usually more expensive to operate in. Moreover, the higher the number of hospital beds and skilled nursing facilities, the lower the marginal cost, which is consistent with the finding that these factors determine the relative bargaining power of managed-care firms when setting reimbursement rates to providers (Ho 2009).

Table 14 presents estimates for marginal costs of advertising. The estimates show that local TV advertising costs increase an insurer's marginal cost of advertising and that different firms potentially have different costs of advertising, possibly because the firms face different resource constraints..

7 Counterfactual Experiments

With the estimated model, we conduct counterfactual analyses to understand the impacts of advertising on the MA market and how incentives for risk selection affect insurers' advertising decisions.

7.1 Ban of Advertising

In this counterfactual analysis, we simulate an equilibrium of the model where advertising is banned. The simulation has two purposes. First, we investigate how advertising affects the choices made by consumers and insurers, and how it affects over-payments by the government. Second, we study how much advertising can account for the selection of healthier individuals into MA.

In implementing this counterfactual analysis, we force each insurer's advertising quantity to zero and let insurers re-optimize their premiums. The results are presented in Table 15. We refer to the observed equilibrium in the data as the baseline. The ban on advertising decreases overall MA enrollment by 4% and decreases demand for insurers having above-average advertising expenditures in the baseline by 9%. Although a decrease in demand would usually lead to a lower premium, the ban on advertising does not have a large effect on premiums, which decrease by less than a dollar on average. The negligible effect of advertising on premiums results from the fact that advertising attracts relatively healthy individuals, which lower the costs of providing insurance. With the ban, MA enrollees become less healthy on average, resulting in a larger increase in average health expenditures for insurers having a relatively large amount of advertising in the baseline. For these insurers, an increase in average expected Medicare claims cost is about \$14, which is about 43% of the average premium charged by these insurers. Such an increase in the cost of providing insurance will offset incentives to lower premiums that result from the reduction in demand caused by the lack of advertising.

Table 16 presents the results on consumers' welfare. We calculate two different measures of consumers' surplus. In the first measure, we include the effects of advertising on utility whereas we exclude these effects in the second measure. The first measure of welfare is consistent with the informative and complementary view of advertising.[39] The informative view holds that advertising provides information about the existence of a product or (unobserved) characteristics of a product that is difficult to be unobserved before consuming the product. As mentioned in the section for the demand model, the effect of advertising on indirect utilities in the model will capture an increase in expected utility due to advertising.[40] The complementary view holds that consumers receive a higher utility from a product when the product is advertised, which reflects a positive image or greater prestige generated by advertising (Stigler and Becker 1977; Becker and Murphy 1993). Therefore, according to these views, advertising will have a direct impact on an individual's indirect utility from an insurer. When consumers' surplus is calculated according to these views of advertising, we find that consumer welfare decreases because consumers do not receive utility from advertising with the ban and because the ban does not reduce premiums much. The second measure of welfare is supposed to capture the part of utility derived from insurer characteristics other than advertising, which is consistent with the persuasive view of advertising. This view holds that advertising does not add any real value to consumers (Bagwell, 2007). When consumers' welfare is calculated according to the persuasive view, we find that advertising increases consumers' welfare because advertising just distorts a consumer's decision according to the persuasive view. However, the welfare could have increased even more if the ban on advertising had decreased premiums by a greater amount.

Now we turn to the second purpose of this counterfactual analysis, which is to investigate

[39] For a discussion of different views of advertising and their welfare implications, see a survey by Bagwell (2007).

[40] For examples, see Stigler (1961); Nelson (1974); Butters (1977); Schmalensee (1977); Grossman and Shapiro (1984); Kihlstrom and Riordan (1984); and Milgrom and Roberts (1986).

how much advertising accounts for the selection of healthier individuals into MA (which is called "advantageous selection", as opposed to adverse selection). In the baseline, MA enrollees are healthier than traditional Medicare enrollees. According to Table 17, the average health status of enrollees in traditional Medicare, in terms of Medicare claims cost, is higher than that of MA enrollees by \$60.6. The difference in average health status between the two groups decreases by 15% with the ban on advertising. This means that advertising accounts for 15% of advantageous selection into MA, and that the rest of the selection can be explained by preference heterogeneity for MA plans. In other words, although preference heterogeneity is a more important determinant of advantageous selection into MA, advertising by MA insurers reinforces the direction of selection.

Because advertising reinforces advantageous selection into MA, it leads to over-paying of capitation payments to MA plans. In the data, MA plans are over-paid even for a random Medicare beneficiary, as reported in Table 16. A reason for this over-payment is that capitation payments were higher than average traditional Medicare costs during this period. Moreover, capitation payments are calculated based on Medicare costs of beneficiaries in traditional Medicare, who are less healthy than MA enrollees. Because over-payments exist even with a random selection into MA, we calculate additional over-payments caused by a non-random selection into MA and compare how these additional over-payments change with the ban on advertising. We find that advertising accounts for 19% of additional over-payments per MA enrollee, and that the rest of the average additional over-payment is attributable to preference heterogeneity between healthy and unhealthy individuals for MA.

7.2 Risk Adjustment

In this counterfactual analysis, we simulate the effects of a perfectly risk-adjusted capitation payment on the MA market equilibrium in order to investigate how incentives for risk selection affect an insurer's choices. A perfectly risk-adjusted capitation payment is a capitation payment that perfectly accounts for variation in health expenditures across individuals having different health statuses. In this counterfactual analysis, let $\widetilde{cap}_{ct}(h)$ denote the new capitation payment in county c in year t that directly depends on an individual's health status h in terms of Medicare claims cost. We assume that:

$$\widetilde{cap}_{ct}(h) = h + const_{ct}. \tag{14}$$

That is, the difference between a capitation payment to an MA insurer and an individual's health status is constant for individuals having different health statuses. An important choice we need to make in this counterfactual analysis is the choice of $const_{ct}$ because it determines the overall generosity of a capitation payment. In order to make the results of this counterfactual analysis comparable to the baseline, we choose $const_{ct}$ to be the average of the over-payments per MA enrollee in each county-year in the baseline. That is, noting that $cap_{ct}(z)$ is a capitation payment in the baseline that depends on individual characteristic z,

$$const_{ct} = E[cap_{ct}(z) - h | d_{ct}(z) = 1].$$

Expectation is taken over individual characteristics z, and $d_{ct}(z)$ is an indicator that equals one if an individual with characteristic z chooses any MA plan in county c in year t in the baseline. This new capitation payment structure changes amounts of over-payments for individuals with different h but keeps the average over-payment unchanged.

We simulate insurers' premiums and advertising quantities in the new environment, and the results are presented in Table 18. The risk-adjusted capitation payments have large effects on insurers' choices. The average advertising expenditure decreases by 30.7%, and the average premium increases from \$32.4 to \$51.1. The results are similar for insurers whose advertising expenditures were above the average in the baseline. The average advertising expenditure by these insurers decreases by 27.8%, and the average premium increases from \$32.4 to \$63.5.

The large decrease in advertising expenditure results from a decrease in marginal profits from enrolling healthy individuals. With the perfect risk-adjustment considered in this counterfactual analysis, capitation payments decrease for healthy individuals and increase for unhealthy individuals. Because advertising has a greater effect on healthier individuals, the perfect risk-adjustment will result in a decrease in marginal profit from an additional unit of advertising, which will lead to a decrease in advertising spending. This finding highlights the importance of risk selection in driving incentives for MA insurers to advertise.

The decrease in revenues from healthy individuals due to the perfect risk-adjustment also leads to increases in premiums. Given our finding that healthy individuals prefer MA more than less healthy individuals even without advertising, MA enrollees are relatively healthy even with the lower advertising expenditure caused by the perfect risk-adjustment. Because the risk-adjustment reduces revenues from enrolling healthy individuals for MA insurers, the insurers increase premiums to compensate for the decrease in revenues. Another factor that contributes to the increase in premiums is that unhealthier individuals are less sensitive to premiums. Because unhealthy individuals now become more profitable to insure, insurers will have incentives to increase premiums to exploit their relative insensitivity to premiums.

Due to the decrease in advertising and the increase in premiums, overall MA enrollment decreases by about 9%, and MA enrollees become less healthy on average. The average over-payment per MA enrollee does not change very much because the constant term in (14) was chosen to be equal to the average over-payment in the baseline. However, the average over-payment for insurers having above-average advertising in the baseline decreases because their enrollees are healthier than those of other insurers because they still advertise more than other insurers even in the new environment. The increase in premiums results in a reduction in consumers' welfare, which is presented in Table 19. Because the magnitude of the increase in premiums is large, consumers' welfare decreases, regardless of individual health status and whether we include the effects of advertising on utility. The changes in insurers' choices due to the risk-adjustment also leads to a less healthy pool of MA enrollees, which results in a decrease in the difference in health status between enrollees in MA and enrollees in traditional Medicare by 11%. Lastly, the average additional over-payment in the new environment does not change because the constant term in (14) was chosen to match the average over-payment in the baseline.

8 Conclusion

This is the first paper to quantify the effects of advertising on risk selection and competition in health insurance markets and to investigate how incentives for risk selection affect insurers' advertising expenditures. We document strong incentives for risk selection by insurance companies in MA due to an imperfect risk adjustment of capitation payments, and we also show how the incentives for risk selection vary over different regions. We present descriptive evidence that MA insurers advertise more in regions where risk selection is more profitable. For the main analysis, we develop and structurally estimate an equilibrium model that incorporates strategic advertising by insurers. The estimates suggest that advertising increases overall demand with a larger effect on healthier individuals. With a counterfactual analysis where advertising is banned, we find that advertising accounts for 15% of the selection of healthier individuals into MA. By reinforcing the selection of healthier individuals into MA, advertising reduces the costs of MA insurers and keeps premiums from increasing although advertising increases demand for MA insurers. By implementing a perfectly risk-adjusted capitation payment, moreover, we also find that incentives for risk selection can account for about 30% of advertising spending in the data, which highlights an important link between advertising and risk selection.

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A Appendix

A.1 Constructing Health Status

In our analysis, an individual's health status is measured as expected Medicare Parts A and B claims cost if the individual were to receive insurance from traditional Medicare (Medicare Parts A and B). In order to construct the variable, we use the individual-level data. Because individuals in MA are not directly covered by traditional Medicare, information on Medicare Part A and B claims is available only for those in traditional Medicare. Therefore we need to impute predicted Medicare costs for MA enrollees. Our construction of the health status variable has two steps:

1. First, using beneficiaries in traditional Medicare, we estimate two equations that relate Medicare claims costs to an extensive list of health status and demographic characteristics.

2. We calculate predicted claims cost for traditional Medicare enrollees using the estimates. We impute the predicted Medicare claims costs for MA enrollees in the data, using their observed health and demographic characteristics and the estimates obtained in the first step.

First Step In the first step, we estimate two equations that relate an individual's realized Medicare claims cost to an extensive list of health and demographic variables. In the first equation, we estimate the probability that an individual ever incurs positive Medicare claims cost. Approximately 5.6% of individuals have zero claims cost in a given year, and we account for the possibility of zero health expenditure using the following logistic regression:

$$Prob(y > 0|x) = \frac{\exp(x\beta_1)}{1 + \exp(x\beta_1)}. \tag{15}$$

y denotes an individual's Medicare claims cost, and x is a vector of health and demographic characteristics. For x, we include an extensive list of health variables such as self-reported health status, whether an individual has difficulties in activities of daily living (ADL) and instrumental activities of daily living (IADL), and histories of diseases such as cancer, heart disease, diabetes, etc. We also include the average Medicare claims cost for each county and year to control for regional differences in health care costs. In the end, we include 76 variables in x. Parameter β_1 is estimated with maximum likelihood, and the results are presented in Table 21.

Using the second equation, we estimate the relationship between an amount of Medicare claims cost and health characteristics for individuals having positive claims costs. We estimate the following equation:

$$\begin{aligned} \log(y) &= x\beta + \epsilon \\ \epsilon &\sim N(0, (z\gamma)^2) \end{aligned}$$

where y and x are the same as in the first equation; and z is a subset of x that includes self-reported health status, whether an individual is living in a skilled nursing facility, average Medicare claims cost for each county, and interaction terms between county-level average Medicare claims costs and other variables in Z. We estimate parameters β and γ with the method of moments. The first set of moments is:

$$E[\log(y)|x, y > 0] = x\beta_2.$$

The second set of moments is:

$$E[y|z, y > 0] = \exp\left(x\beta_2 + \frac{(z\gamma)^2}{2}\right).$$

The right-hand side of the second condition is derived from the assumption that ϵ is normally distributed. The first set of moments will pin down β_2, and the second set of moments will pin down γ. The estimates are presented in Table 22.

Note that we make an implicit assumption here that ϵ is independent of the logistic error term for equation (15). This means that a correlation between $Prob(y > 0|x)$ and $E[y|x]$ only depends on x, not on the error terms. Although it is possible to allow for correlated error term, we make such an assumption for simplicity.

Second Step Given estimates of parameters $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\gamma}$, we calculate predicted Medicare claims cost for each individual. Because y is not observed only for individuals in MA, we have to impute predicted Medicare claims for MA enrollees using the estimates. An important assumption we make for the imputation is that x contains all relevant health characteristics of an individual. That is, individuals in MA and traditional Medicare are not different in unobserved health, conditional on x. This assumption implies that ϵ is a purely random shock to claims costs, and individuals do not select on ϵ when choosing between MA and traditional Medicare. Without this assumption, the imputation of predicted Medicare claims costs for MA enrollees will not be valid. Although it is possible that x may not capture all relevant health characteristics, the large number of variables in x would minimize the role of unobserved health characteristics.

We calculate predicted Medicare claims cost in the following way:

$$\begin{aligned} E[y|z] &= Prob(y > 0|x) \times E[y|x, y > 0] \\ &= \frac{\exp(x\hat{\beta}_1)}{1 + \exp(x\hat{\beta}_1)} \times \exp\left(x\hat{\beta}_2 + \frac{(z\hat{\gamma})^2}{2}\right). \end{aligned}$$

A.2 List of Plan Characteristics Included in the Model

Table 2: Plan Characteristics Included in Analysis

Mean Utility	Interaction with Health Status
Generic drug	Drug coverage (Generic + Brand)
Brand drug	Inpatient copay up to 5 Days
Unlimited Drug Coverage	Nursing Home copay to 20 Days
Dental	Emergency care copay
Routine Eye Exam	Primary care physician copay
Glasses	Specialist copay
Hearing Aids	Quality: ease of getting referral to specialists
Hearing Exam	Quality: overall rating of health plan
Nursing Home Copay up to 20 Days	Dummy for Secure Horizon
Nursing Home Copay up to 100 Days	Dummy for United Healthcare
Emergency Care Copay	Dummy for Kaiser Permanente
Emergency Care Coinsurance	Dummy for Blue Cross Blue Shield
ER Worldwide Coverage	Dummy for Aetna
Primary Physician Copay	Dummy for Humana
Primary Physician Coinsurance	Dummy for Health Net
Specialist Copay	
Specialist Coinsurance	
Inpatient Copay up to 5 Days	
Inpatient Copay up to 90 Days	
Inpatient Coinsurance	
Quality: ease of getting referral to specialists	
Quality: overall rating of health plan	
Quality: overall rating of health care received	
Quality: doctors communicate well	
Number of plans offered by a Firm-county-year	

Note: Dummies for different brands are implicitly included in insurer-county fixed effects in the mean utility.

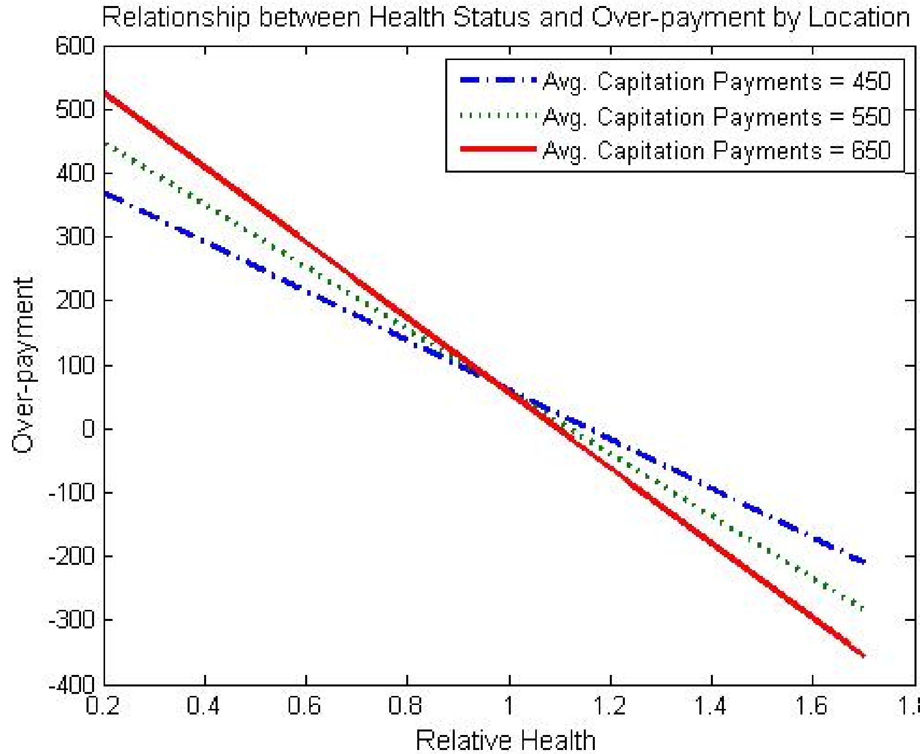
A.3 Figures and Tables

Table 3: Capitation Payments and Demographic Characteristics

Dep. Var: Capitation Payment Paid for an MA Enrollee		
Variables	Coefficient	Std. Err.
Female	219.3**	(88.20)
Male with Age 65–69	-165.1**	(81.18)
Female with Age 65–69	-286.2***	(34.91)
Male with Age 70–74	-67.81	(80.72)
Female with Age 65-69	-209.1***	(33.11)
Male with Age 75–79	36.74	(80.45)
Female with Age 75–79	-140.0***	(31.20)
Male with Age 80–84	97.85	(80.00)
Female with Age 80–84	-88.06***	(29.93)
Male with Age 85–89	135.2*	(80.32)
Female with Age 85–89	-24.38	(29.44)
Male with Age 90–94	117.7	(83.38)
Female with Age 90–94	-51.31*	(31.05)
Age	-17.34***	(1.671)
Living in a Nursing Home	-414.0	(287.0)
Medicaid Eligible	-97.88*	(56.98)
Avg. Capitation	-1.485***	(0.180)
Avg. Capitation × Female	-0.272***	(0.0341)
Avg. Capitation × Nursing Home	1.664***	(0.502)
Avg. Capitation × Medicaid	0.624***	(0.0885)
Avg. Capitation × Age	0.0336***	(0.00243)
Observations	8,020	
R-squared	0.822	

Note: Avg. Capitation means the average capitation payment in county of residence for each individual, which is extracted from the Medicare State-County-Plan databases 2000–2003. The regression was run only with the sample of MA enrollees.
Source: Medicare Current Beneficiary Survey 2000–2003; Medicare State-County-Plan databases 2000–2003.

Figure 1: Relationship between Health Status and Over-payment by Location



Note: Relative health $= \frac{\text{Expected Health Expenditure}}{\text{County-level Medicare Costs}}$; median of relative health $= 0.6$; mean of relative health $= 0.89$. These plots were generated based on a regression of an amount of over-payment on relative health, average capitation payment in each county, interaction between relative health and average capitation payment, as well as other control variables that determine a capitation payment. The regression results are reported in Table 6. The plots were generated for an individual of age 75 that is not eligible for Medicaid and not living in a nursing home. The plots show that over-payments are greater for healthier enrollees and that over-payments for the healthy are greater in regions with higher average capitation payments.

Table 4: Summary Statistics at County Level

	CTY w/o ad	CTY w/ ad $<$ \$250k	CTY w/ ad $\geq$\$250k
No. of county-year	800	1264	385
Population (age $\geq$ 65)/ county	15,589	34,220	113,047
% MA enrollment	0.07	0.21	0.32
Monthly Capitation Payments / enrollee	\$520.3	\$534.2	\$613.3
Monthly Medicare costs/ enrollee	\$458.4	\$459.1	\$566.3
No. of Firms	1.30	2.63	5.19
No. of Firms with Advertising	0	1.88	4.43
Premium for Firms w/ ad $<$ mean	\$57.8	\$42.7	\$29.9
Premium for Firms w/ ad $>$ mean	n/a	\$39.0	\$47.4
Avg Market Shares for Firms w/ ad $<$ mean	0.05	0.08	0.06
Avg Market Shares for Firms w/ ad $>$ mean	n/a	0.12	0.11
Total Number of Insurer-county-year	893	2648	1440

Note: 'CTY w/o ad' means counties belonging to a local advertising market having no advertising spending; 'CTY w/ ad $<$ \$250k' means counties belonging to a local advertising market where total advertising spending is below \$250,000; and 'CTY w/ ad $\geq$ \$250k' means counties belonging to a local advertising market where total advertising spending is at least \$250,000.
Source: AdSpender 2000–2003; CMS state-county-plan files 2000–2003.

Table 5: Incentives for Risk Selection

Self-reported Health Status		Market Categories		
		CTY w/o ad	CTY w/ ad < $250k	CTY w/ ad ≥$250k
Excellent or Very Good	Capitation ($)	435.1	450.4	520.0
	Health Expenditures ($)	213.2	225.2	257.9
	Over-payments ($)	221.9	225.2	262.1
Good	Capitation ($)	440.0	464.3	536.4
	Health Expenditures ($)	394.9	385.4	444.7
	Over-payments ($)	45.1	78.9	91.7
Fair or Poor	Capitation ($)	454.6	470.5	549.4
	Health Expenditures ($)	721.3	736.1	912.7
	Over-payments ($)	-266.7	-265.7	-363.3
Number of Observations		2729	7594	7729

Note: 'CTY w/o ad' means counties belonging to a local advertising market without any advertising spending; 'CTY w/ ad < $250k' means counties belonging to a local advertising market where total advertising spending is below $250,000; and 'CTY w/ ad ≥ $250k' means counties belonging to a local advertising market where total advertising spending is at least as large as $250,000.
Source: Medicare Current Beneficiary Survey 2000–2003; AdSpender 2000–2003

Table 6: Relationship between Health Status and Over-payment by Location

Dependent Variable = Expected Over-payment		
VARIABLES	Coefficient	Std. Err.
Relative Health	69.37***	(15.31)
Relative Health × Avg Capitation Payment at the county-level	-1.012***	(0.0278)
Avg Capitation Payment at the county-level	0.990***	(0.0214)
Observations	31,756	
R-squared	0.977	

Note: Other Controls are age, age-squared, age-cubed, Medicaid status, and whether one lives in a nursing home.

Table 8: Health Status and Insurer Choice by Medicare Beneficiaries

County Category	Insurer Category		
	Traditional Medicare	MA w/ Ad < \$150K	MA w/ Ad > \$150K
Counties with total ad spend = 0	0.936	0.930	N/A
Counties with total ad spend ∈ (0, \$250K]	0.918	0.811	0.701
Counties with total ad spend> \$250K	0.952	0.767	0.726
Counties with avg capitation < \$500	0.919	0.799	0.726
Counties with avg capitation∈ [\$500,\$600]	0.918	0.818	0.722
Counties with avg capitation > \$600	0.989	0.742	0.722
Overall	0.934	0.798	0.722

Note: The reported number in each cell is the average relative health status of enrollees in each insurer and market category.
Source: Medicare Current Beneficiary Survey 2000–2003.

Table 7: Relationship between Advertising and Capitation Payments

	(1)	(2)	(3)	(4)
Dependent Variable	Ad Qty		Ad Expenditure	
Avg. Capitation	1.257***	1.032*	0.568***	0.693**
	(0.247)	(0.590)	(0.128)	(0.294)
Population (65 <)	7.94e-05**	3.94e-05	0.000139***	2.48e-05
	(4.03e-05)	(0.000109)	(2.09e-05)	(5.50e-05)
Local TV Ad Cost	-68.71**	-94.20*	17.75	-13.37
	(34.16)	(48.08)	(17.71)	(23.98)
No. of Competitors	13.60*	-20.59*	2.291	-9.311
	(7.244)	(11.58)	(3.755)	(5.788)
Fixed Effect	Insurer	Insurer - Ad market	Insurer	Insurer - Ad market
Year FE	Yes	Yes	Yes	Yes
R-squared	0.094	0.039	0.185	0.060
Observations	1,035	1,035	1,035	1,035

Note: The dependent variable in specification (1) and (2) is advertising quantity by an MA insurer in a local advertising market in a year, and that in specification (3) and (4) is advertising spending in a local advertising market in a year. Specification (1) and (3) have market-invariant insurer fixed effects, whereas specification (2) and (4) allow for market-specific insurer fixed effects. Average capitation payments in a local advertising market is the average across average capitation payments in each county belong to the advertising market, weighted by population of each county. The variable, number of competitors, is constructed in a similar way by taking the average across counties with a county population as a weight.

Table 9: Estimates for Key Parameters in Utility

Variables	Estimates	Std. Err.
Ad effects (ϕ_0)	0.040	(0.063)
$\log(rh_i)$ $\times$Ad effects (ϕ_1)	-0.036**	(0.018)
Curvature of Ad effects (ϕ_2)	0.012**	(0.005)
$\log(rh_i)$ $\times$Outside option (part of λ)	0.233**	(0.097)
Premium (α_0)	-0.002***	(0.0005)
$\log(rh_i)$ $\times$Premium (α_1)	8.0e-4	(7.4e-4)

Table 10: Elasticity of Demand with Respect to Advertising and Premiums

Semi-Elasticities of Demand	Ad ($1,000)	Price ($1)
Overall Semi-elasticity	0.063%	-0.25%
Semi-elasticity for $h_i < 25\%$	0.092%	-0.28%
Semi-elasticity for $h_i > 25\%$ and $h_i < 50\%$	0.070%	-0.26%
Semi-elasticity for $h_i > 50\%$ and $h_i < 75\%$	0.050%	-0.24%
Semi-elasticity for $h_i > 75\%$	0.020%	-0.22%

Table 11: Estimates for Parameters in Mean Utility (δ_{jmt})

VARIABLES	Estimates	Std. Err.
Generic drug	0.423***	(0.147)
Brand drug	0.275***	(0.0399)
Unlimited Drug Coverage	0.105***	(0.0355)
Dental	-0.0318	(0.0362)
Routine Eye Exam	-0.172***	(0.0278)
Glasses	-0.134***	(0.0349)
Hearing Aids	0.204***	(0.0340)
Hearing Exam	0.0982***	(0.0370)
Nursing Home Copay up to 20 Days	-0.00173***	(0.000590)
Nursing Home Copay up to 100 Days	-0.00209***	(0.000383)
ER Copay	-0.000702	(0.00108)
ER Coinsurance	-0.108***	(0.0125)
ER Worldwide Coverage	0.145***	(0.0417)
Primary Physician Copay	-0.00111	(0.00247)
Primary Physician Coinsurance	-0.0446***	(0.00679)
Specialist Copay	-0.00262*	(0.00137)
Specialist Coinsurance	0.0424***	(0.00631)
Inpatient Copay up to 5 Days	9.36e-05	(6.99e-05)
Inpatient Copay up to 90 Days	0.00159***	(0.000275)
Inpatient Coinsurance	-0.0581***	(0.00454)
Quality: ease of getting referral to specialists	-0.00873	(0.0159)
Quality: overall rating of health plan	0.202***	(0.0177)
Quality: overall rating of health care received	-0.0731***	(0.0235)
Quality: doctors communicate well	-0.0378*	(0.0206)
Number of plans offered by a Firm-county-year	0.0268***	(0.00311)
Year FE	Yes	
Firm - county FE	Yes	

Table 12: Estimates for Preference Heterogeneity

Variables	Estimates	Std. Err.
Health×Drug coverage	-0.112	(0.140)
Health×Inpatient copay	-1.2e-5	(2.3e-4)
Health×Skilled nursing facility copay	0.002	(0.001)
Health×Emergency care copay	0.002	(0.002)
Health×Primary care physician copay	-2.3e-4	(0.007)
Health×Specialist copay	-0.005	(0.004)
Health×How easy to get a referral for SP	-0.066**	(0.034)
Health×Overall rating health plan	0.016	(0.037)
Health×Secure Horizon	-7.5e-4	(0.135)
Health×United Healthcare	0.016	(0.119)
Health×Kaiser Permanente	-0.083	(0.142)
Health×Blue Cross Blue Shield	-0.107	(0.074)
Health×Aetna	0.013	(0.102)
Health×Humana	-0.149	(0.140)
Health×Health Net	-0.107	(0.142)
Medicaid×Outside option	1.464***	(0.189)
Employer benefits×Outside option	2.049***	(0.048)
Age×Outside option	-0.107	(2.695)
Age-squared×Outside option	0.046	(0.017)

Table 13: Estimates for Marginal Costs of Providing Insurance

Variables	Estimates	Std. Err.
Expected Health Expenditure (h)	0.865***	(0.0320)
Dental	21.00***	(4.532)
Routine eye exam	10.39**	(4.972)
Skilled nursing facility copay	-0.669***	(0.0985)
Emergency care copay	-1.027***	(0.221)
Primary care doctor copay	1.878***	(0.403)
Specialist copay	-0.860***	(0.236)
How easy to get a referral for SP	17.30***	(2.638)
Overall rating health plan	-13.42***	(3.021)
Population density	0.00337***	(0.000221)
Percentage of urban population	0.365***	(0.0565)
No. of hospital beds	-0.395***	(0.0910)
No. of skilled nursing facility	-37.97***	(10.88)
Insurer Dummy	Yes	
Year Dummy	Yes	

Table 14: Estimates for Marginal Costs of a Unit of Advertising

Variables	Estimates	Std. Err.
Local TV Advertising Cost	0.491***	(0.123)
Secure Horizon	0.039	(0.135)
United Healthcare	-0.271***	(0.119)
Kaiser Permanente	0.572***	(0.142)
Blue Cross Blue Shield	-1.123***	(0.074)
Aetna	-0.272***	(0.102)
Humana	-0.103	(0.140)
Health Net	-.557***	(0.142)
Standard Deviation of ζ (σ_{ξ})	1.356***	(0.579)
Year Dummy	Yes	

Table 15: Ban on Advertising

		Baseline	Ban on Ad
All firms (N = 4864)	Share of beneficiaries	0.243	0.236 (-4%)
	Average Premium ($)	32.4	31.5
	Average Health Status ($)	402.3	408.5
	Over-payment per enrollee ($)	136.9	130.8 (-4%)
Insurers with Above-average ad (N = 881)	Share of beneficiaries	0.101	0.092 (-9%)
	Average Premium ($)	32.4	31.1
	Average Health Status ($)	407.4	421.1
	Over-payment per enrollee ($)	150.4	137.6 (-8%)

Note: A share of beneficiaries is the fraction of the total Medicare beneficiaries who choose any MA insurers or insurers with above-average advertising spending.

Table 17: Health Compositions in traditional Medicare vs MA (Ban on Advertising)

	Baseline	Ban on Ad
Health Status of Enrollees in traditional Medicare ($)	462.9	460.3
Health Status of Enrollees in MA ($)	402.3	408.5
Difference between traditional Medicare and MA($)	60.6	51.8 (-15%)
Over-payments per MA enrollee ($)	136.9	130.8 (-4%)
Over-payments per a random beneficiary ($)	104.3	104.3
Additional over-payments per MA enrollee ($)	32.6	26.5 (-19%)

Note: The numbers in the third row is the difference between the first and second row, and an additional over-payment is the difference between an over-payment per MA enrollee and over-payment per a random beneficiary.

Table 16: Consumer's Surplus with a Ban on Advertising

		Baseline	Ban on Ad
Case 1	$rh_i < 25\%$	\$112.8	\$108.3
	$rh_i > 75\%$	\$135.7	\$133.9
	Overall	\$116.6	\$114.8
Case 2	$rh_i < 25\%$	\$101.9	\$108.3
	$rh_i > 75\%$	\$131.6	\$133.9
	Overall	\$109.5	\$114.8

Note: In case 1, the calculation of consumer surplus included the effects of advertising on utility. In case 2, however, we exclude the effects of advertising on utility in the calculation of consumer surplus. That $rh_i < 25\%$ refers to the group of individuals whose relative health status rh_i is below the 25th percentile in the distribution of relative health status. That is, this group is the healthiest. That $rh_i > 75\%$ refers to the group of individuals whose relative health status rh_i is above the 75th percentile in the distribution of relative health status. That is, this group is the most unhealthy.

Table 18: Risk Adjustment

		Baseline	Risk Adjustment
All firms (N = 4864)	Ad expenditure (\$)	78.2K	53.7K (-30.7%)
	Premium (\$)	32.4	51.1
	Share of Beneficiaries	0.243	0.221 (-9%)
	Expected health expenditures (\$)	402.3	406.7
	Over-payment per enrollee (\$)	140.2	140.2
Firms with Above-average ad (N = 881)	Ad expenditure (\$)	392.4K	282.4K (-27.8%)
	Premium (\$)	32.4	63.5
	Share of Beneficiaries	0.101	0.091 (-8.8%)
	Expected health expenditures (\$)	407.4	411.9
	Over-payment per enrollee (\$)	150.4	145.4

Table 19: Consumer's Surplus with Risk Adjustment

		Baseline	Risk Adjustment
Case 1	$rh_i < 25\%$	\$112.8	\$96.8
	$rh_i > 75\%$	\$135.7	\$128.3
	Overall	\$116.6	\$110.9
Case 2	$rh_i < 25\%$	\$101.9	\$99.1
	$rh_i > 75\%$	\$131.6	\$129.5
	Overall	\$109.5	\$107.3

Note: In case 1, the calculation of consumer surplus included the effects of advertising on utility. In case 2, however, we exclude the effects of advertising on utility in the calculation of consumer surplus. That $rh_i < 25\%$ refers to the group of individuals whose relative health status rh_i is below the 25th percentile in the distribution of relative health status. That is, this group is the healthiest. That $rh_i > 75\%$ refers to the group of individuals whose relative health status rh_i is above the 75th percentile in the distribution of relative health status. That is, this group is the most unhealthy.

Table 20: Health Risk Compositions in traditional Medicare vs MA (Risk Adjustment)

	Baseline	Risk Adjustment
Health Status of Enrollees in traditional Medicare (\$)	462.9	459.8
Health Status of Enrollees in MA (\$)	402.3	406.1
Differences between traditional Medicare and MA(\$)	60.3	53.7 (-11%)
Over-payments per MA enrollee (\$)	136.8	138.5
Over-payments per a random beneficiary (\$)	104.3	138.5
Additional over-payments per MA enrollee (\$)	32.6	0

Note: The numbers in the third row is the difference between the first and second row, and an additional over-payment is the difference between an over-payment per MA enrollee and over-payment per a random beneficiary.

Table 21: Logit Regression for Positive Medicare Claims Cost

Dependent Variable: Dummy for Positive Medicare Claims Cost		
Variables	Coefficient	Std. Err.
Black	-0.781***	(0.0764)
Hispanic	-0.540***	(0.0957)
Living in a nursing home	1.924**	(0.815)
Health status: excellent	-0.286*	(0.153)
Health status: very good	0.00109	(0.149)
Health status: good	0.159	(0.145)
Health status: fair	0.354**	(0.147)
Difficulty using phone	-0.123	(0.106)
Difficulty light housework	-0.0820	(0.134)
Difficulty heavy housework	0.384***	(0.0809)
Difficulty preparing meals	0.545***	(0.162)
Difficulty shopping	-0.0864	(0.125)
Difficulty handling bills	-0.307**	(0.123)
Difficulty bathing	0.187	(0.131)
Difficulty dressing	-0.283*	(0.167)
Difficulty eating	-0.282	(0.206)
Difficulty stooping	-0.156	(0.109)
Difficulty walking	-0.0743	(0.0826)
Difficulty using toilet	0.304*	(0.178)
History with skin cancer	0.533***	(0.0726)
History with other cancers	0.622***	(0.0783)
History of high blood pressure	0.583***	(0.0501)
History of heart attack	0.219***	(0.0845)
History of angina pectoris	0.342***	(0.0963)
History of other heart conditions	0.420***	(0.0757)
History of stroke	0.253***	(0.0896)
History of rheumatoid arthritis	0.0372	(0.0972)
History of arthritis	0.411***	(0.0500)
History of diabetes	0.675***	(0.0827)
County-level Medicare cost	-0.00965***	(0.00182)
County-level Medicare cost × Nursing home	0.00123	(0.00139)
County-level Medicare cost × Age	0.000131***	(2.42e-05)
Medicaid	0.745***	(0.0961)
Employer-sponsored insurance benefit dummy	0.363***	(0.0550)
Observations	44,088	
Pseudo R-squared	0.158	

Note: Other controls included are dummy variables for various groups of age, gender, interactions of age and gender, income, education, marital status, self-reported health status compared to a year ago. The number of variables included in this logit regression is 78. Source: Medicare Current Beneficiary 2000–2004.

Table 22: Regression of Medicare Claims Costs on Health Characteristics

Dependent Variable: Medicare Claims Cost		
Variables	Coefficient	Std. Err.
Black	-0.0420	(0.0333)
Hispanic	-0.0149	(0.0461)
Living in a nursing home	0.513***	(0.194)
Health status: excellent	-0.580***	(0.0525)
Health status: very good	-0.347***	(0.0489)
Health status: good	-0.140***	(0.0469)
Health status: fair	-0.0758*	(0.0457)
Difficulty using phone	-0.188***	(0.0374)
Difficulty light housework	0.0469	(0.0396)
Difficulty heavy housework	0.204***	(0.0238)
Difficulty preparing meals	0.143***	(0.0447)
Difficulty shopping	-0.00237	(0.0380)
Difficulty handling bills	-0.0195	(0.0411)
Difficulty bathing	0.199***	(0.0380)
Difficulty dressing	0.0639	(0.0463)
Difficulty eating	-0.0271	(0.0633)
Difficulty stooping	-0.111***	(0.0335)
Difficulty walking	0.0477*	(0.0264)
Difficulty using toilet	0.108**	(0.0493)
History with skin cancer	0.240***	(0.0199)
History with other cancers	0.437***	(0.0214)
History of high blood pressure	0.104***	(0.0181)
History of heart attack	0.228***	(0.0256)
History of angina pectoris	0.224***	(0.0263)
History of other heart conditions	0.284***	(0.0208)
History of stroke	0.124***	(0.0266)
History of rheumatoid arthritis	0.147***	(0.0270)
History of arthritis	0.174***	(0.0180)
History of diabetes	0.348***	(0.0210)
County-level Medicare cost	0.00109*	(0.000627)
County-level Medicare cost × Nursing home	0.00108***	(0.000282)
County-level Medicare cost × Age	1.87e-05**	(7.95e-06)
Medicaid	0.0820**	(0.0323)
Employer-sponsored insurance benefit dummy	-0.0112	(0.0179)
Observations	41,603	
R-squared	0.249	

Note: For this regression, only the individuals with positive Medicare claims costs are included. Other controls included are dummy variables for various groups of age, gender, interactions of age and gender, income, education, marital status, self-reported health status compared to a year ago. The number of variables included in this logit regression is 78.
Source: Medicare Current Beneficiary 2000–2004.