2014

# Essays on Private Medicare Insurance Markets

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### Abstract

This dissertation consists of two essays in economics of industrial organization on private Medicare insurance markets. In the first chapter, together with Naoki Aizawa, we study the incentives for private health insurers to use advertising to attract healthy individuals in the market for private Medicare plans called Medicare Advantage (MA). Using data on the advertising expenditures of MA plans, individual-level and county-level MA enrollment, we document a large difference in an insurer's potential profits from healthy vs. unhealthy individuals. We then develop and estimate an equilibrium model of the MA market, which incorporates strategic advertising by insurers. Parameter estimates show that advertising has much larger effects on the demand of the healthy. We find that advertising accounts for 15% of the selection of healthier individuals into Medicare Advantage. In the second chapter, I study how consumer search frictions affect adverse selection and competition in the Medicare Supplement Insurance (Medigap) market. Using data on individual-level and market-level Medigap enrollment and claim costs, I estimate an equilibrium model of the Medigap market, which incorporates consumer search frictions and adverse selection. Parameter estimates show that search frictions are significant and that unhealthy consumers tend to face greater search costs. I find that the correlation between search costs and health risks reduces the extent of adverse selection by keeping unhealthy consumers with high search costs outside the market. In a counterfactual experiment where the government provides more information on available options, I find that the extent of adverse selection increases and that healthy individuals become worse off.


### Degree Type
Dissertation

### Degree Name
Doctor of Philosophy (PhD)

### Graduate Group
Economics

### First Advisor
Hanming Fang


### Keywords
Adverse selection, Advertising, Insurance, Medicare, Search Frictions


### Subject Categories
Economics

ESSAYS ON PRIVATE MEDICARE INSURANCE MARKETS

You Suk Kim

A DISSERTATION

in

Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2014

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ESSAYS ON PRIVATE MEDICARE INSURANCE MARKETS

*To my beloved family, teachers and friends.*

# Acknowledgments

I am greatly indebted to my advisor Hanming Fang for his guidance and support. His continuous help and encouragement have been essential in every stage of my graduate studies. No words can express my deep respect toward him. I would like to thank my dissertation committee members, Katja Seim, Robert J. Town and Kenneth I. Wolpin. Their insights and enthusiasm in economics have inspired me and helped shape my research greatly. I am enormously grateful for their valuable comments. I thank all of the Penn Economics faculty for being great examples of dedicated researchers and teachers.

I am also grateful to Jaesung Choi, N. Mattis Gornemann, Ilwoo Hwang, Eunyoung Shim, Minchul Shin, Dongho Song, Suryun Rhee and Chamna Yoon for their friendship. They made my life at Penn much more enjoyable. Special thanks go to Naoki Aizawa. I feel extremely blessed to have him as my friend and co-author.

My deepest thanks go to my beloved family. They are my source of confidence and hard work. I could not have made it this far without the unconditional love and support from my wife, Aileen. Her patience and support was crucial especially in completing last years of my graduate studies. I cannot thank her enough for everything she has done for me. I also thank my parents for trusting my choices of pursuing a doctoral degree and believing in me. They are the best parents anyone could ask for. Last but not least, I am also thankful to my parents-in-law and my sister's family for their support and love.

**ABSTRACT**

ESSAYS ON PRIVATE MEDICARE INSURANCE MARKETS

You Suk Kim

Hanming Fang

This dissertation consists of two essays in economics of industrial organization on private Medicare insurance markets. In the first chapter, together with Naoki Aizawa, we study the incentives for private health insurers to use advertising to attract healthy individuals in the market for private Medicare plans called Medicare Advantage (MA). Using data on the advertising expenditures of MA plans, individual-level and county-level MA enrollment, we document a large difference in an insurer's potential profits from healthy vs. unhealthy individuals. We then develop and estimate an equilibrium model of the MA market, which incorporates strategic advertising by insurers. Parameter estimates show that advertising has much larger effects on the demand of the healthy. We find that advertising accounts for 15% of the selection of healthier individuals into Medicare Advantage. In the second chapter, I study how consumer search frictions affect adverse selection and competition in the Medicare Supplement Insurance (Medigap) market. Using data on individual-level and market-level Medigap enrollment and claim costs, I estimate an equilibrium model of the Medigap market, which incorporates consumer search frictions and adverse selection. Parameter estimates show that search frictions are significant and that unhealthy consumers tend to face greater search costs. I find that the correlation between search costs and health risks reduces the extent of adverse selection by keeping unhealthy consumers with high search costs outside the market. In a counterfactual experiment where the

government provides more information on available options, I find that the extent of adverse selection increases and that healthy individuals become worse off.

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## Chapter I

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

## 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 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

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

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

[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.

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, 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, researchers 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

[3]For examples, see Chiappori and Salanie (2000) for automobile insurance, Finkelstein and McGarry (2006) for long-term care insurance, and Fang et al. (2008) for Medicare supplement insurance.

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

[4]For other works in this literature, see Bajari et al. (2011); 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).

(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.

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

[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.

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 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]

[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.

# 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 AdSpender 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 insurers' 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 pay-

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

ment 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 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.

[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.

### 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 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 expendi-

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

tures 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 $\psi_{mt}$. 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 $\psi_{mt}$ equal to the fraction of the population that is at least 65 years old in each advertising market. Although the choice of $\psi_{mt}$ is not likely to lead to a perfect measure of advertising expenditures for MA, the choice of $\psi_{mt}$ 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 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

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

[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.

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

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

is usually the most popular.[16] [17] For the current version of this paper, 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

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

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 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

[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.

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, $\delta_j$ denotes insurer fixed effects which are invariant over local advertising markets ($m$). In the second specification, $\xi_{jm}$ 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,

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

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 beneficiaries 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 $\phi_0$ 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 heterogeneous effects on individuals with different $rh_i$ ($\phi_1$). We assume that the effects of advertising diminish in its quantity by assuming that $ad_{jt}$ enters $g(\cdot)$ in logarithm. Parameter $\phi_2$ 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

[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.

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 $\alpha_1$. $x_{jct}$ 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 MA plan, and how well doctors

[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.

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 $\beta_1$ 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, $\epsilon_{ijct}$ 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

[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.

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

With the functional-form assumption on $\epsilon_{ijct}$, 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

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

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

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. $\psi_j$ 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, $\eta_{jct}$ is a firm-county-year-specific shock to marginal costs that is constant across individuals with different $h$. We assume that $\eta_{jct}$ 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

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

$x_{jmt}^{ad}$ 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] $\zeta_{jmt}$ is a shock to the marginal cost, which

[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.

is also known by all insurers in a media market, but unobserved by researchers. We assume that $\zeta_{jmt} \sim N(0, \sigma_\zeta^2)$.[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 $p_{jct}$:

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

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.

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

[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.

# 5 Identification and Estimation

For the discussion of identification and estimation of the model, we define $\theta$ as a vector that contains all parameters in the model such that $\theta = (\theta^d, \theta^s)$. $\theta^d$ and $\theta^s$ 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: $\theta_1^d$ and $\theta_2^d$. We define $\theta_1^d$ to be parameters that enter 'mean utility' $\delta_{jct}$, which is a part of $u_{ijct}$ that does not depend on individual characteristics. Precisely,

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

$\theta_2^d$ is defined as parameters for interaction terms between insurer characteristics and individual characteristics. We let $\phi_2$, which determines diminishing returns of advertising effects, be a part of $\theta_2^d$. Berry et al. (1995) show that given a value for $\theta_2^d$, 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 $\theta_1^d$ is estimated using equation 6. A well-known problem regarding identification of $\theta_1^d$ is that the unobserved characteristic ($\Delta\xi_{jct}$) and two endogenous variables in the 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 $\delta^*_{jct}(\theta_2^d)$ on the observed variables in (6) will result in inconsistent estimates of $\theta_1^d$.

Although the endogeneity problem causes challenges in identification, fixed effects $\overline{\xi_{jc}}$ in $\delta_{jct}$ 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:

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

$\Gamma$ 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 $\theta_2^d$ is an individual's insurer choice from the MCBS (the individual-level data). Parameter $\theta_2^d$ will be identified by variation in the characteristics of insurers chosen by individuals having different characteristics. Identification of $\theta_2^d$ 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 $\theta_2^d$ is the parameter that determines the heterogeneous

[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.

effect of advertising depending on an individual's health status ($\phi_1$), which captures the effect of advertising on risk selection. A potential concern in identifying $\phi_1$ 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 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:

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

[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.

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 (13). The first order condition for optimal pricing (4) is equivalent to the following condition:

$$\begin{aligned} \frac{Q_{jct} + \int_z (p_{jct} + cap_{ct}(z)) \frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z)}{\frac{\partial Q_{jct}}{\partial p_{jct}}} &= \frac{\int_z c_{jct}(h) \frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z)}{\frac{\partial Q_{jct}}{\partial p_{jct}}} \\ &= x_{jct}\gamma_1 + w_{ct}\gamma_2 + H(q_{jct}, F_{ct})\gamma_3 \quad (9) \\ &\quad +\psi_j + \eta_{jct} \quad (10) \end{aligned}$$

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:

$$E[\eta_{jct}|x_{jct}] = 0 \text{ and } E[\eta_{jct}|w_{ct}] = 0. \tag{11}$$

These assumptions will identify parameters $\gamma_1$ and $\gamma_2$.

However, we cannot have a similar condition for parameter $\gamma_3$ because $H(q_{jct}, F_{ct})$ is potentially endogenous to $\eta_{jct}$. Because an insurer's choice of $p_{jct}$ will be directly dependent on $\eta_{jct}$ in the model, and because $p_{jct}$ will determine $q_{jct}(z)$, variable $H(q_{jct}, F_{ct})$ may be correlated with $\eta_{jct}$. This endogeneity problem necessitates an instrument that is correlated with $H(q_{jct}, F_{ct})$, but not with $\eta_{jct}$. 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 $\eta_{jct}$, which leads to the identifying assumption for $\gamma_3$ such that

$$E[\eta_{jct}|FFS_{ct}] = 0. \tag{12}$$

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

$$\zeta_{jmt} \begin{cases} = \log\left(\sum_{c\in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}}\right) - x^{ad}_{jmt}\gamma_{ad} & \text{for } ad_{jmt} > 0 \\ \geq \log\left(\sum_{c\in m} \frac{\partial \pi_{jct}}{\partial ad_{jmt}}\right) - x^{ad}_{jmt}\gamma_{ad} & \text{for } ad_{jmt} = 0 \end{cases} \tag{13}$$

As is clear in (13), 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 $\zeta_{jmt}$ 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 the first order conditions (13). 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 $f_\zeta$ and $F_\zeta$ are the pdf and cdf of $\zeta$. Then the moment conditions for advertising cost are

$$\begin{aligned} \frac{\partial \log(\Gamma)}{\partial \gamma_{ad}} &= 0 \\ \frac{\partial \log(\Gamma)}{\partial \sigma_\zeta} &= 0. \end{aligned} \tag{14}$$

An alternative approach, not taken in this paper, is to set-identify $\gamma_{ad}$ using the moment inequality method as in Pakes et al. (2011), which will result in an upper

[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 $\eta$ when estimating the parameters in the marginal cost of providing insurance because there are no inequality optimality conditions for pricing.

and lower bound for $\gamma_{ad}$. 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 $\zeta$ 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 $\zeta$ can lead to point-identification of parameters at the cost of a stronger assumption on unobservable $\zeta$. However, the moment inequality method is not completely free of an assumption on $\zeta$ 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 $\zeta$ 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 $\Psi_d(\theta^d) = G_d(\theta^d)'WG_d(\theta^d)$ where $W$ is a weighting matrix. Our estimation routine searches for $\theta^d$ that minimizes $\Psi_d(\theta^d)$. Evaluation of $G_d(\theta^d)$ can be broken into the following steps for each choice of $\theta^d$:

1. Given $\theta^d$, 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 $\theta^d$ 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 $\theta^d$, the supply model is estimated using moments (11), (12), and (14).

## 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 $\phi_0$ is not large enough to be statistically significant, $\phi_0 + \phi_1 \log(rh_i)$ will be larger than $\phi_0$ 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 higher premium, and that healthier individuals are less sensitive to premium although the estimate for $\alpha_1$ 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.

[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.

[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.

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 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

[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.

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,

[38] As a robustness check, we plan to consider the possibility that individuals make a choice at the

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 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

plan-level, not at the insurer-level. See footnote 17 for details.

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

[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).

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 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 overpaying 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 overpayment 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:

$$\widetilde{cap}_{ct}(h) = h + const_{ct}. \tag{15}$$

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 (15) 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 (15) 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.

## Chapter II

# Consumer Search Frictions, Competition and Adverse Selection in Health Insurance Markets: Evidence from Medigap

## 1 Introduction

Medicare is the universal, public health insurance for Americans aged 65 and older. There also exist markets for private health plans that supplement Medicare, including Medicare Supplement (Medigap), Medicare Advantage and Medicare Part D. About 50% of Medicare beneficiaries purchase at least one of these plans. A well-functioning of these private markets depends on consumers' ability to make informed decisions based on comparison-shopping, which will foster competition among insurance companies. However, many Medicare beneficiaries have diminished cognitive capacities associated with aging (Fang et al., 2008), and only about 50% of them have ever used the Internet.[41] Such consumer search frictions are likely to influence the decisions of Medicare beneficiaries in the markets for private health plans.

A popular type of private health plan for Medicare beneficiaries is Medicare Supplement insurance, also called Medigap, which covers out-of-pocket expenditures from Medicare. Indeed, the market for Medigap shows an indication of search frictions.

[41]Source: the author's calculation from Medicare Current Beneficiary Survey 2003–2005

Although Medigap plans are homogenous by regulation, Medigap premiums are not only highly dispersed, but also charged well above claims (Maestas et al. 2009; Lin and Wildenbeest 2013; Starc 2012). These findings are consistent with predictions by theoretical search models that search frictions lead to the price dispersion of homogeneous products and firms charging prices above their costs.[42] The goal of this paper is to investigate how search frictions affect consumers' choice, insurers' pricing and welfare in the Medigap market.

A potential correlation between health status and search cost needs to be considered in studying the effects of search frictions in the Medigap market. Compared to healthy individuals, less healthy individuals tend not to use the Internet and/or have diminished cognitive capacities.[43] If unhealthy individuals tend to have high search costs, then these individuals are more likely to make less ideal choices, i.e., purchasing an otherwise identical plan with a higher premium or not purchasing a Medigap plan. In contrast, healthy individuals are more likely to purchase cheaper Medigap plans. Therefore, a correlation between health status and search frictions will determine which type of individuals (healthy vs. unhealthy) enroll in a given Medigap plan. Because a regulation in the Medigap market prohibits insurers from charging different premiums based on health statuses, a premium will ultimately depend on the composition of the health statuses of the enrollees in a given plan, which is influenced by search frictions.

For the main analysis, I develop and structurally estimate an equilibrium model of the market, incorporating consumer search frictions and their correlation with health status. On the demand side, a consumer's preference for a Medigap plan depends on

[42] For examples, see Burdett and Judd (1983), Carlson and McAfee (1983), and Stahl (1989).

[43] Evidence for the correlation between the Internet use and health status will be presented in the section for descriptive statistics in this paper. For evidence regarding cognitive ability, see Fang et al. (2008).

the plan's characteristics and the consumer's characteristics including health status as well as other demographic characteristics. In the model, a consumer does not necessarily have the full information about the entire Medigap plans and incurs search cost to expand a choice set. In addition, I allow for the possibility that an individual's search cost depend on the individual's health status. On the supply side, Medigap insurers choose the optimal premiums to maximize profits given other insurers' pricing decisions. A plan's costs depend on health statuses of its enrollees, and thus an insurer's pricing decision takes into account its impact on types of consumers that would enroll with the insurer.

I estimate the model with firm-level and individual-level data. The firm-level data provide information on plan characteristics, aggregate market shares, and average cost of claims incurred for each plan. The individual-level data provide information on demographic characteristics and whether an individual has a Medigap plan. The estimates show that search frictions are significant, and unhealthy individuals are more likely to have higher search costs. Those with "excellent" or "very good" self-reported health status forgo about 16% of an average premium due to search frictions, whereas those whose health status is "good" or below forgo an amount as large as an average premium. As a result, the unhealthy are more likely than healthier individuals to skip purchasing a Medigap plan even though the estimates suggest that they have a higher willingness to pay for Medigap coverage. I also find that although search frictions give firms an incentive to raise premiums by making demand inelastic, high search costs of the unhealthy lower a premium.

Using the estimated model, I simulate the effects of a policy that reduces search frictions by providing consumers with information about available options in the Medigap market. With this policy, I assume that a consumer becomes fully aware of all available options. In a partial equilibrium setting where premiums are fixed at the level observed in the data, all consumers in the market benefit from this new policy because of the larger choice set induced by the policy. When I allow for Medigap plans to adjust their premiums in response to this policy, however, I find that not every consumer benefits. Because search costs are larger for the unhealthy, who have a higher willingness to pay for a Medigap plan, the policy induces adverse selection into the Medigap market. As a result, the overall price for Medigap increases although the demand becomes more elastic without search frictions. Overall Medigap enrollment increases, but the increase mostly comes from the unhealthy. The welfare of the healthy decreases slightly, whereas that of the unhealthy substantially increases. These findings suggests that efforts to increase access to information on available choices should be accompanied by a policy that reduces the effects of the subsequent adverse selection.

This paper builds on prior work that empirically studies demand for insurance plans and competition in health insurance markets.[44] Among many previous works, this paper is closely related to Starc (2012), who studies adverse selection and imperfect competition in the Medigap market. She focuses on adverse selection in the intensive margin, which refers to the selection of less healthy individuals into an otherwise identical plans charging a higher premium. By estimating a model of the Medigap market without considering search frictions, she finds that less healthy individuals are less sensitive to premiums, which explains the observed adverse selection in the intensive margin. This paper is different from Starc (2012) because of its consideration of search frictions and because of its focus on selection in both the intensive and extensive margin. The observed adverse selection in the intensive margin can be explained by a correlation between search cost and health status. Moreover,

[44]For examples in this literature, see Bajari et al. (2011); 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).

the correlation can also explain the selection of healthier individuals into the Medigap market in the extensive margin (Fang et al., 2008), which is not a main focus of Starc (2012). Another closely related paper in the literature is Handel (2011), who studies an interaction between switching cost and adverse selection in the context of employer-based health insurance markets. Although he also studies a similar type of frictions in a health insurance market, Handel's framework lacks competition between insurance companies, which is an important element defining the Medigap market.

This paper also contributes to a body of literature that empirically investigates adverse selection in insurance markets. Standard models on insurance markets usually predict adverse selection, which means that riskier consumers choose more comprehensive plans, causing the equilibrium prices of these plans to rise (e.g., Rothschild and Stiglitz 1976). However, previous research often finds evidence against adverse selection. For example, Chiappori and Salanie (2000) do not find evidence for adverse selection in a market for automobile insurance. Moreover, Finkelstein and McGarry (2006) and Fang et al. (2008) find that individuals with lower risks are more likely to purchase long-term care insurance and Medigap, respectively. This pattern of selection is called advantageous selection, and primary reasons for advantageous selection are that an individual's characteristics other than risks also determine an insurance purchase decision, and that these characteristics are often correlated with risks in a way that results in advantageous selection. Finkelstein and McGarry (2006) and Fang et al. (2008) find that risk aversion and diminished cognitive abilities are such characteristics, respectively. Based on the result on cognitive ability found by Fang et al. (2008), this papers considers a consumer's search cost and its correlation with health status as an explanation for the observed advantageous selection in the Medigap market.

This paper is also related to the literature on consumer search frictions. Most of existing theoretical and empirical papers on consumer search frictions have not considered the possibility that an individual's search cost is correlated with the individual's characteristics that have a direct impact on a firm's cost.[45] Even previous research that studies the Medigap market with consumer search frictions do not consider the possibility (e.g., Maestas et al. 2009; Lin and Wildenbeest 2013). Without the correlation between search cost and health status, the effects of search frictions will be just limited to the size of demand. Then a model without the correlation will not be able to take into account the potential effects of search frictions on a firm's cost and its subsequent equilibrium response.

The paper is organized as follows. Section 2 describes the Medigap market in greater detail and presents descriptive statistics from data. Section 3 outlines the model, and Section 4 describes identification and estimation of the model . Section 5 and 6 provides the estimates and model fits, respectively. Section 6 presents counterfactual policy analysis which studies the role of search frictions in the Medigap market, and Section 7 concludes.

# 2 The Medigap Market and Data

## 2.1 The Medigap Market

Medicare provides health insurance coverage for people who are 65 and older in the U.S. However, it has substantial cost-sharing provisions such as deductibles, coinsurance and copayments. For example, Medicare Part B, which covers outpatient services, requires 20% copayments for services with no stop-loss. As a result, Medi-

[45] For examples of theoretical works, see Burdett and Judd (1983); Carlson and McAfee (1983); Stahl (1989). For examples of empirical works, see Allen et al. (2012); De los Santos et al. (2012); Hong and Shum (2006); Hortaçsu and Syverson (2004)

care beneficiaries still face a large amount of out-of-pocket medical expenditure risks, and Medigap insurance arose to meet the demand to cover the gap in coverage of Medicare.

An important feature of the Medigap market is that Medigap plans are homogeneous by regulation. With the passage of the Omnibus Budget Reconciliation Act of 1990, Medigap plans were standardized as in Figure 2. Each plan falls into one of ten types – labeled plans A though J.[46] Medigap plans of different types differ in insurance coverage. As clear in Figure 2, a Medigap plan A provides the least generous coverage, and a Medigap plan J provides the most comprehensive coverage. However, Medigap plans are contractually identical within each type. Plans of the same type do not only offer the same coverage as specified in Figure 2 but also are identical in terms of provider networks. Unlike managed care health insurance companies, Medigap insurers do not form their own provider networks. Patients can receive medical care from any doctors or hospitals as long as they accept Medicare payments for procedures they perform. Therefore there is little room for a Medigap insurer to differentiate its plans from other Medigap insurers' plans.

Although one can expect that the Medigap market would be very competitive because of the lack of differentiations among plans, the Medigap market is still highly concentrated, and premiums for plans of the same type are dispersed. As reported in Table 23, the average market shares of the largest insurer in each state is about 50%, and the smallest market share of the largest insurer in a state is more than 20%. Moreover, the two largest insurers in a typical state control about 70% of market shares. For an example, consider market shares for Medigap plan Cs in Pennsylvania

[46]This is standardization before the introduction of Medicare Part D in 2006, which provides coverage for prescription drug expenditures. After the introduction of Medicare Part D, Medigap plans H,I and J, which provided prescription drug coverage, were no longer offered. The data used for this paper comes from years before 2006.

presented in Table 24. Almost 90% of those who chose a Medigap plan C in the state purchased it from one of the two largest companies. Table 24 also shows that different insurers charge very different premiums for the same coverage. Although some companies charges a similar or lower premium than United Healthcare, demand for them is significantly lower than demand for United Healthcare. These results indicate that the Medigap market is not very competitive despite the standardization of plans.

Another important feature of the Medigap market is an open enrollment period during which medical underwriting is prohibited. The open enrollment period runs for six months, beginning when consumers turn 65 and enroll in Medicare Part B. During the open enrollment period, an insurance company must accept a consumer's application regardless of pre-existing conditions and can vary premiums only on the basis of age, gender, and smoking status. Therefore consumers of different health risks would pay the same premium for a Medigap plan although their costs to an insurer will be very different. Although this regulation on premiums would lead to adverse selection, Fang et al. (2008) find evidence for advantageous selection in the Medigap market, which means healthier individuals are more likely to purchase Medigap. Regardless of a direction of selection, however, the open enrollment period will make a consumer's selection an important factor that determines a Medigap insurer's cost and eventually its pricing strategy. In order to study how a correlation between search cost and health status affects the Medigap market, this paper focuses a consumer's choice during the open enrollment period.

## 2.2 Data

I use both state- and individual-level data for my analysis. State-level information comes from two different sources. First, I use information on a premium for each state-insurer-plan type from Weiss Rating for the year 2003. This dataset provides information on the premium charged by each Medigap plan in each state for 65, 75 and 85 year-olds. I use the premium information only for 65-year-olds because I focus on a consumer's initial choice of a Medigap plan during the open enrollment period. I also use state-level data from the National Association of Insurance Commissioners (NAIC). The data set is a regulatory administrative database, which contains information on the total earned premium, quantity of new policies sold, and claims cost incurred for each the state-insurer-plan type. An important feature of the data is that the NAIC aggregates the information into three year periods. For example, the 2005 data contain information on new policies sold from 2003–2005. In this paper, I use the NAIC data for the year 2005. Combining the two different datasets, I use data from Weiss Rating for information on the premium for each state-insurer-plan type. I do not use information on premiums from the NAIC data because the data do provide information on premiums not for 65-year-olds only. Instead the data provide information about the average earned premium per new enrollee, and a new enrollee may include individuals aged much more than 65. For the market share and claims cost for each state-insurer-plan type, I use information from the NAIC data.

There are a few issues in combining the two datasets. The first problem is that the NAIC data are aggregated into three year period 2003-2005, as mentioned above. This means that the NAIC does not provide information on Medigap enrollments and claims cost only for the year 2003 although the information on premiums is for Medigap plans offered in 2003. Without data at more finer level than what the

NAIC data provides, I have to assume that markets in the period from 2003–2005 are stationary and that a market share for each plan did not change over the three-year period. Although market shares are very likely to change over the three-year period, it seems unlikely that certain firms rapidly gained or lost market shares over the period. Because the Medigap market with the regulations on the standardization and open enrollment period had been around for a long time, dating back to early 1990s, it is reasonable to assume that the Medigap market was stationary in the period.

The second problem is that the NAIC data provide information on newly sold plans in the period, which may not only include individuals older than 65. Since most of new Medigap purchasers are likely to be consumers in an open enrollment period, I assume that observed market shares in the data set are equal to market shares for 65-year-old consumers. Another related problem is that the NAIC data on the average claims cost incurred by enrollees in each of newly sold Medigap plans were calculated using all new enrollees in each plan who may be older than 65. Because those aged more than 65 are more likely to be less healthier and incur more claims cost, the NAIC data may overstate actual claim costs for 65-year-old enrollees. To deal with this problem, I assume that a ratio of the average claims cost to the premium charged by each plan is the same for 65-year-old consumers and older consumers. Then I calculate the ratio using the NAIC data on the average premium and claims cost for each plan and multiply the ratio with the observed premium of each plan in the Weiss data in order to calculate the average claim cost for 65-year-old enrollees for each Medigap plan.

I augment the aggregate-level data with individual-level data from the Medicare Current Beneficiary Survey (MCBS) 2003–2005. The MCBS is a survey of a nationally representative panel of Medicare beneficiaries that is linked to administrative records from Medicare. It provides a rich set of demographic information such as age, health status, income, private insurance coverage and so on. Since I focus on a consumer's initial choice of a Medigap plan at age of 65, it would be ideal to use samples only with age of 65. Unfortunately, the MCBS does not have many observations that are 65 years old. Thus, I use observations with age of 68 or under.[47] From the MCBS, I use a demographic information such as income and self-reported health status. Importantly, the MCBS also provides variables that can be related to an individual's search costs such as an individual's Internet usage. I also retrieve information on whether an individual purchased a private supplemental insurance plan from the MCBS. However, the data set does not provide information about which Medigap plan an individual chose. Lastly, I also use information on how much a supplemental plan paid for an individual's medical expenditures in a given year.

## 2.3 Discussion of the Data

Since this paper focuses on a correlation between search cost and health status, an ideal data set would provide information on search behavior of individuals having different health statuses. Unfortunately, the available data are not ideal with this respect, and I discuss how I overcome the challenges. First, the available datasets do not provide information on an individual's search behaviors or information about which Medigap plans were in his choice set when he made a decision. The lack of such information makes it impossible for a researcher to infer about search frictions directly from data. Therefore I construct a model of consumer search and estimate the model with the available datasets on consumer choices and aggregate enrollment and claims for each plan. Using the model whose parameters are estimated to rationalize

[47] An implicit assumption made is that a joint distribution of individual choices and characteristics is the same across ages from 65-68.

observed choice patterns in the data, I will be able to infer about search frictions.[48]

Another limitation of the datasets is that I do not observe an individual choice of a specific Medigap plan. Unfortunately, the MCBS provides information only on whether an individual purchased a Medigap plan, but not information on which Medigap plan type or insurer the individual chose.[49] I overcome this problem with the data on the average claims cost for each plan. Because of the standardization of Medigap plans, it is reasonable to assume that claims for an enrollee in a plan will depend only on the plan's type, state-level medical care cost and the enrollee's health risks, but not on insurer-specific factors. The assumption implies that differences in average claims costs of two plans of the same type in the same state result from differences in overall health risks of enrollees in two plans. This means that the aggregate data on claims cost can provide information about how consumers having different health statuses sort into different plans.[50]

## 2.4 Descriptive Statistics

Table 25 presents descriptive statistics about the ten standardized Medigap plan types. In terms of market share, about a half of Medigap enrollees choose a Medigap plan F, and the type is the most popular among the ten types. Plan Cs and plan Js follow plan Fs in terms of shares of Medigap enrollees. Plan As have the lowest average annual premium among the ten types because they provide the least comprehensive coverage, and Plan Js have the highest average annual premium because they provide

[48] Usually it is difficult to have information on an individual's product search, the approach taken in this paper is quite common in the papers that structurally estimate a model of consumer search frictions. For examples, see Hortaçsu and Syverson (2004) and Hong and Shum (2006).

[49] The MCBS has a variable that is supposed to contain information on which Medigap plan type an individual chose. Unfortunately, a very large number of observations have missing values for this variable, which makes it difficult to use the variable for the analysis.

[50] This type of inference about individual heterogeneity from aggregate data is in a similar spirit to Petrin (2002).

the most comprehensive coverage.

Descriptive statistics from the MCBS in Table 26 shows that Medigap enrollees are quite different from those without Medigap.[51] A notable fact is that individuals having Medigap tend to be healthier than individuals not having Medigap, which is opposite to the selection pattern predicted by theoretical models of adverse selection (Rothschild and Stiglitz, 1976). The observed selection pattern is called advantageous selection, and Fang et al. (2008) finds that one of sources of advantageous selection into the Medigap market results is income. Table 26 shows that individuals with higher incomes are more likely to purchase a Medigap plan. Because those with higher incomes tend to be healthier and are more likely to purchase Medigap, advantageous selection can result from income to some extents. Table 26 also shows that individuals using the Internet are also more likely to purchase a Medigap market. Using the Internet would reduce the cost associated with gathering information, thereby lowering search cost of an individual's using the Internet and increasing demand for Medigap. Moreover, the Internet variable is highly correlated with an individual's health status. Table 27 shows that those with better health are more likely to use the Internet, which indicates a potential correlation between search cost and health status. Then the difference in search costs of individuals having different health statuses can also be a factor that induces advantageous selection into the Medigap market.

In order to investigate how these variables affect a Medigap purchase decision

[51] To measure a consumer's health status, I use self-reported health status of a consumer from MCBS. In the original MCBS data, self-reported health status has five categories: excellent, very good, good, fair and poor. In the actual estimation, I only allowed for three different health status. First, I put together the excellent and very good health status into a group, which will be referred to as the excellent group from now on. Second, I leave the group with good health status as it is. Lastly, I put together the fair and poor group into one group, which will be referred to as the poor group from now on. I made this change for the excellent group because the consumers with excellent and very good health status did not exhibit significant differences in terms of their observed choices and claim costs. The change for the poor group was made because there were not many people with poor health status for each state market.

more precisely, I run a regression of a dummy variable for purchasing a Medigap plan on observable individual characteristics. The results are reported in Table 28, which shows that consumers who have higher incomes and use the Internet are more likely to purchase a Medigap market. However, the coefficient for health status is not positive enough to be statistically significant, which implies that an individual's health status is not a predictor for a Medigap purchase decision despite controlling for other important factors. This is because the regression does not control for an individual's cognitive ability, which Fang et al. (2008) find an important source of advantageous selection into the Medigap market.[52] Because healthier individuals are less likely to have diminished cognitive abilities, and because individuals without diminished cognitive abilities are more likely to purchase Medigap, omitting a variable related cognitive ability is likely to lead to biased estimates of coefficients for health statuses. In the main analysis of this paper, I discuss how I deal with this issue of not having a measure of an individual's cognitive ability.

In addition, the aggregate data on the average claims cost for each plan show how individuals having different health statuses sort into different plans. In order to investigate difference in health statuses of enrollees in otherwise identical plans charging different premiums, I run the following regression:

$$acc_{ljm} = \beta p_{ljm} + \delta_j + \tau_{lm} + \epsilon_{ljm}$$

where $acc_{ljm}$ and $p_{ljm}$ are the average claims cost and premium of plan type $l$ of insurer $j$ in state $m$; $\delta_j$ is the fixed effect for each insurer; $\tau_{lm}$ is the fixed effect for

[52] The reason why an individual's cognitive ability is not controlled for here is because the MCBS does not provide direct information on cognitive ability. Fang et al. (2008) combine the MCBS and Health and Retirement Survey (HRS) for their analysis and retrieve measure on an individual's cognitive ability from the HRS. I plan to combine the information from the HRS for revision of this paper.

each combination of a plan type and state. Table 29 the display results from the regression, which show that the estimate of $\beta$ is positive and statistically significant. Because of the fixed effects included in the regression, the estimate of $\beta$ indicates that more expensive plans are associated with higher claims with all other being equal. However, the estimate of $\beta$ cannot be interpreted as a causal effect of premiums on claims cost due to likely reverse causality. A plan's premium would be determined by an insurer in an equilibrium, and the plan's cost would be an important determinant of the premium. However, Starc (2012), who also studies the Medigap market with nearly identical data, shows that the relationship between premiums and claims are causal using an instrument for a premium. This result implies that an insurer charging a higher premium is more likely to have less healthy enrollees, conditional on plan type and state, which is consistent with less healthy individuals having higher search costs.

# 3 Model

## 3.1 Demand Side

For the demand side, I incorporate consumer search frictions into a discrete choice framework. A consumer chooses to enroll in one of Medigap plans in his choice set, which is endogenously determined by the consumer's search behavior. The outside option of not purchasing a Medigap plan is always included in a consumer's choice set, regardless of whether the consumer searches or not.

### 3.1.1 Utility

Each market $m$ is defined as a state. An insurer $j$ in market $m$ offers a subset of the ten standardized plans $L_{jm}$, which I assume is exogenous to the model. Indirect utility of a consumer, with characteristic $z$ and plan-level preference shock $\epsilon$, from choosing a Medigap plan with letter $l$ from insurer $j$ in market $m$ is:

$$\begin{aligned} u_{ljm}(z,\epsilon) &= \sum_{l'=A}^{J} \beta_{l'} \mathbf{1}\left[l=l'\right] + \alpha_y p_{ljm} + \sum_{n=1}^{2} \beta_{h,n} 1\left[h=n\right] + b_j \\ &\quad + \mu_m + \xi_{ljm} + \epsilon_{ljm} \\ \alpha_y &= \alpha_0 + \alpha_1 y \end{aligned} \tag{16}$$

When a consumer chooses not to purchase a Medigap plan, the consumer chooses the outside option in the model. Since I can only identify a consumer's utility from an inside good relative to the outside option, I normalize utility from the outside good to be:

$$u_{0m}(z,\epsilon) = \epsilon_{0m}.$$

$u_{ljm}(z,\epsilon)$ depends on dummy variables for each plan letter $l$, premium ($p_{ljm}$), health status ($h$), income ($y$), brand effects ($b_j$), market fixed effects ($\mu_m$), and unobserved demand shock for each plan ($\xi_{ljm}$). Individual characteristics $(h, y)$ are included in $z$. Because Medigap plans are standardized, their characteristics are identical across insurance companies. Accordingly, the dummy variable for each plan type $l'$, $\mathbf{1}\left[l=l'\right]$, does not vary over insurers. An individual's preference for a Medigap plan depends on the individual's characteristics: $h$ and $y$. An individual's health status $h$ affects the overall utility for any Medigap plan relative to the outside option. An individual's income $y$ affects marginal disutility from a premium. As mentioned in a previous section, I use three different categories for health status: excellent, good, and poor. I refer to excellent, good and poor health status as 1, 2 and 3, respectively. For example, $\beta_{h,1}$ is the coefficient for those with excellent health status.

Although Medigap plans are supposed to be homogeneous, I allow for the possibility that perceived qualities of plans are different by including brand effects $b_j$. I specify that some large insurers have different brand effects $b_j$. For example, the largest Medigap insurance company, United Healthcare offer AARP-branded Medigap plans, which may raise a consumer's willingness to pay for the insurer's Medigap plans (Starc, 2012). It is also possible that Medigap plans offered by insurers that are members of Blue Cross Blue Shield have such brand effects, and these insurers tend to be large indeed. In the end, I let the following insurers have different $b_j$: United Healthcare; Blue Cross Blue Shield, Mutual of Omaha, Banker's Insurance, State Farm, and United American. This means that other smaller insurers' $b_j$ is normalized to zero, and that their plans of the same type are homogeneous.

I control for differences in demand for any Medigap plan across different states with market fixed effects $\mu_m$. That is, $\mu_m$ measures the utility for a Medigap plan in general relative to the utility from the outside option in each state. In order to see what $\mu_m$ captures, it is necessary to understand what kind of options comprise of the outside option. The outside option is the choice of not purchasing a Medigap plan, which includes not only choosing the basic Medicare Parts A and B but also choosing a Medicare Advantage plan offered by private insurers, which replaces an individual's Medicare coverage. Medicare Advantage plans have very different penetration rates across states, which reflects heterogeneous preference Medicare Advantage, depending on states. Because a consumer cannot choose both a Medigap plan and Medicare Advantage plan, Medigap plans will face more fierce competition with the outside option in a market with generally strong demand for Medicare Advantage plans. By including the state fixed effects, I control for such differences in Medigap demand across states.

Plan-level demand shocks are captured by $\xi_{ljm}$. Because Medigap plans are standardized and because we include brand effects $b_j$, it is not very likely that $\xi_{ljm}$ captures unobserved plan characteristics. Rather, $\xi_{ljm}$ is likely to be a demand shock. As is standard in a model for differentiated products, I assume that $\xi_{ljm}$ is observed by consumers and insurers when making decisions but is unobserved by a researcher. Lastly, $\epsilon_{ljm}$ is a plan-specific preference shock from a Type I extreme value distribution that is i.i.d across consumers and plans.

### 3.1.2 Search Process

In a standard discrete choice model, a consumer would simply choose an option that maximizes his utility among all available plans in a market. I depart from the standard model by assuming that a consumer does not necessarily know about existence of all available options in a market and that it is costly for a consumer to gather information about his choice set. I assume that a consumer searches for available options in the following way:

1. A consumer in market $m$ randomly draws a choice set $s$ with probability $Pr(s)$ without incurring any search costs.

2. After drawing the initial choice set $s$, he decides whether to search or not, comparing his search costs and gain from searching. If he does not search, he makes a choice within choice set $s$. If he does, then he makes a choice under the full information about his choice set.[53]

[53]It is possible that a consumer actual searching changes the consumer's choice set more gradually in reality. However, the assumption is not too restrictive because it is possible to find some online resources that compare all available Medigap plans. The website for the insurance department of several states offers such information.

Initial choice set $s$ is a subset of all available insurers in a market and always includes the outside option. Let $J_m$ bet the set of all insurers except the outside option in market $m$. Then $s \in S_m \equiv \{x : x = x' \cup \{0\}, \forall x' \subseteq J_m\}$, where '0' represents the outside option. If a consumer makes a choice under choice set $s$, then he can choose any plan offered by insurers in $s$. I specify the probability of meeting with choice set $s$ in the initial stage in the following way:

$$Pr(s) = \left( \prod_{jm \in s} \rho_{jm} \right) \times \left( \prod_{j'm \in J_m \setminus s} (1 - \rho_{j'm}) \right)$$

where $\rho_{jm} \in [0, 1]$ denotes the probability that a consumer meets with $jm$ (firm-market) in the initial stage of the search process. $\rho_{jm}$ captures insurer $jm$'s advantage over other insurers in a consumer's search process. For example, an insurer's strong sale network or advertisement efforts will translate into a high value of $\rho_{jm}$ in the model. The first term represents the probability of meeting with insurers in choice set $s$, and the second term represents the probability of not meeting with insurers which are not in choice set $s$. I specify $\rho_{jm}$ in the following way:

$$\rho_{jm} = \frac{\exp(x_{jm}\beta_x)}{1 + \exp(x_{jm}\beta_x)} \tag{17}$$

where $x_{jm}$ is firm characteristics. For the estimation, $x_{jm}$ is a collection of dummy variables for a variety of firms.

**Search Costs** A consumer with observed characteristics $z$ will search if a gain from searching is greater than his search cost $c$. I assume that $c \sim F_{c|z_{sc}}$ with $c \geq 0$, where $z_{sc}$ is a consumer's observed characteristics that affect his search cost distribution. $z_{sc}$ includes: (i) a dummy variable for whether he has ever used the Internet for services, and (ii) a consumer's self-reported health status. Because the Internet variable is highly correlated with health status, and because a consumer's health status directly affect his search cost distribution, a consumer's search cost can be correlated with health status. In the estimation, I assume $F_{c|z_{sc}}$ is an exponential distribution with parameter $\lambda(z_{sc};\beta) = \beta_{\lambda,0} + z_{sc}\beta_{\lambda,z}$ so that $F_{c|z_{sc}}(c) = 1 - \exp\left(-\frac{c}{\lambda(z_{sc};\beta)}\right)$. The first term $\beta_{\lambda,0}$ is a constant, and $\beta_{\lambda,z}$ is a vector of parameters that determine the effects of an individual's characteristics on the individual's search cost.

A dummy variable for each health status in the search cost parameters is included in order to capture a correlation between health status and search costs that is not captured by the variable for the Internet usage. Although the Internet variable is highly correlated with health status as shown in Table 27, there are likely to be other variables, correlated with health status, which can affect search costs. For example, Fang et al. (2008) find that a decline in cognitive ability is an important factor that lowers an individual demand for Medigap. Since those with a decline in cognitive ability are very likely to be unhealthy, the decline was one of the most important sources that induce advantageous selection into the Medigap market. As Fang et al. (2008) suggests, a plausible way for a cognitive ability to affect an individual's Medigap purchase decision is through search costs. Without a direct measure of cognitive abilities in the individual-level data, the effects of health status on a search cost will capture the effects of cognitive abilities on search cost.

**Gains from Searching** If a consumer searches, then he can make a decision under the full information about the available choices in a market. Therefore utility after searching will be

$$V_m(z,\epsilon) = \max_{l \in L_j, j \in J_m} u_{ljm}(z,\epsilon),$$

where $L_j$ is the set of plan letters offered by insurer $j$, and $J_m$ is the set of all insurers in market $m$. If a consumer does not search, he will have to make a choice under choice set $s \in S_m$ drawn in the initial stage. With choice set $s$, a consumer will receive utility of

$$v_m(s, z, \epsilon) = \max_{l \in L_j, j \in s} u_{ljm}(z, \epsilon).$$

Then gains from searching will be

$$r_m(s, z, \epsilon) = V_m(z, \epsilon) - v_m(s, z, \epsilon).$$

Note that $r_m(s, z, \epsilon) \geq 0$ for any $s \in S_m$ because a consumer makes a choice with a smaller number of options if not searching. Given an initial choice set $s$ and search cost $c$, a consumer will search whenever $r_m(s, z, \epsilon) \geq c$.

### 3.1.3 Demand

Consider the demand for plan $ljm$ from a consumer with observed characteristics $z$, preference shock $\epsilon$, search cost $c$, and initial choice set $s$. Define $d_{ljm}(z, s, \epsilon, c)$ to be an indicator function which equals one when plan $ljm$ is chosen:

$$\begin{aligned} d_{ljm}(z, s, \epsilon, c) &= \mathbf{1}\left[jm \in s\right] \mathbf{1}[r_m(s, z, \epsilon) < c] \mathbf{1}[u_{ljm}(z, \epsilon) = v_m(s, z, \epsilon)] \\ &+ \mathbf{1}\left[jm \notin s\right] \mathbf{1}[r_m(s, z, \epsilon) \geq c] \mathbf{1}[u_{ljm}(z, \epsilon) = V_m(z, \epsilon)]. \end{aligned} \quad (18)$$

This means that there are two possible cases in which a consumer chooses plan $ljm$. The first term represents the case that a consumer does not search and that plan $ljm$ maximizes a consumer's utility among plans in initial choice set $s$. The second term represents the case that although insurer $jm$ is not in $s$, a consumer searches and chooses plan $ljm$. Note that if a consumer searches, he never chooses a plan in initial choice set $s$ because gains from searching is positive only when the optimal plan for the consumer is not in $s$. Then if searching, the consumer will always choose the optimal plan over any plans in $s$.[54]

By integrating $d_{ljm}(z, s, \epsilon, c)$ over $\epsilon$, I can calculate expected demand for each plan given $z, c$ and $s$. Following steps in the appendix, it can be shown that consumer $z$'s expected demand for plan $ljm$ is:

$$q_{ljm}(z) = \sum_{s \in S_m} Pr(s) \int_c \frac{\exp\left(\tilde{u}_{ljm}(z) - c\mathbf{1}\left[jm \notin s\right]\right)}{1 + \sum_{j' \in J_m} \exp\left(\tilde{u}_{lj'm}(z) - c\mathbf{1}\left[j'm \notin s\right]\right)} dF_{sc|z}. \quad (19)$$

Aggregate market shares for each plan $Q_{ljm}$ can be calculated simply by integrating $q_{ljm}(z)$ over $z$:

$$Q_{ljm} = \int_z q_{ljm}(z) dF_z. \quad (20)$$

**Discussion** The search model results in an individual's choice probabilities similar to a standard discrete choice model, given by equation (19). However, an important difference between the model here and standard model is that given initial choice set $s$, a consumer behaves as if the consumer's utilities from plans outside $s$ were lower by the magnitude of search cost $c$. Given initial choice set $s$, an individual must incur search cost $c$ in order to choose a plan outside $s$. Then ex-ante demand for a plan outside $s$ must account for the costly search by reducing the utility from the plan by the magnitude of search cost. Despite the difference between the two models, the demand for plan $ljm$ given $s$ and $c$ has the same expression as derived from the standard multinomial logit model. Thus, mathematical properties of the demand equation are not different from those of the standard demand model for differentiated

[54]This result relies on the assumption that a consumer knows the distribution of utilities including $\epsilon$ from all available plans before searching and that values for $\epsilon$ do not after searching.

products as in Berry et al. (1995). This means that it is possible to invert the equation (20) for aggregate market shares to recover 'mean utility,' which is the part of utility that is constant across individuals. This also implies that the standard estimation method can be applied to the model in this paper.

Another property of $q_{ljm}(z)$ to note is that search frictions affect an individual's demand for insurers, but not the individual's demand for each plan type within an insurer. This is because search frictions affects an individual's information set at the insurer-level, not at the plan-level. In order to see this point, I rewrite the equation (19) in the following way:

$$\begin{aligned}
q_{ljm}(z) &= \sum_{s\in S_m} Pr(s)\int_c \frac{\exp\left(\tilde{u}_{ljm}(z)-c\mathbf{1}\left[jm\notin s\right]\right)}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm\notin s\right]\right)}dF_{sc|z} \\
&= \frac{\exp\left(\tilde{u}_{ljm}(z)\right)}{\sum_{l'\in L_{jm}}\exp\left(\tilde{u}_{l'jm}(z)\right)}\times \\
&\quad \sum_{s\in S_m} Pr(s)\int_c \frac{\sum_{l'\in L_{jm}}\exp\left(\tilde{u}_{l'jm}(z)-c\mathbf{1}\left[jm\notin s\right]\right)}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm\notin s\right]\right)}dF_{sc|z} \qquad (21)\\
&= q_{l|jm}(z)\times q_{jm}(z), \qquad (22)
\end{aligned}$$

where

$$\begin{aligned}
q_{l|jm}(z) &\equiv \frac{\exp\left(\tilde{u}_{ljm}(z)\right)}{\sum_{l'\in L_{jm}}\exp\left(\tilde{u}_{l'jm}(z)\right)}; \\
q_{jm}(z) &\equiv \sum_{s\in S_m} Pr(s)\int_c \frac{\sum_{l'\in L_{jm}}\exp\left(\tilde{u}_{l'jm}(z)-c\mathbf{1}\left[jm\notin s\right]\right)}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm\notin s\right]\right)}dF_{sc|z}.
\end{aligned}$$

The alternative expression of an individual's demand in (22) shows that an individual's demand for a plan type $l$ of insurer $j$ in market $m$ can be broken down into two parts. The first term $q_{l|jm}(z)$ denotes an individual's demand for plan type $l$ given that the individual chooses insurer $jm$; the second term $q_{jm}(z)$ denotes the individual's demand for insurer $jm$; and the unconditional demand for a plan is the product of the two terms.

Such a property of the model implies that search frictions will determine how much an individual is sensitive to a premium when choosing among plans of the same plan type from different insurers. Because an individual with higher search cost cannot easily substitute to plans of other insurers, search frictions will reduce cross-elasticity of demand with respect to premium. However, search frictions will not affect an individual's price-sensitivity for plans within an insurer because an individual can observe all available plans offered by an insurer in a choice set. This property of the model will be exploited in identifying search frictions, which will be discussed in the section for identification.

## 3.2 Supply Side

Given the demand system, an insurer chooses the optimal premiums for their plans that maximize their profit given premiums chosen by other insurers. An insurer's expected marginal cost of insuring an enrollee has two components: claims cost and non-claim costs such as administrative costs. An insurer $jm$'s expected marginal cost of insuring consumer of health status $h$ with plan $l$ is given by:

$$mc_{ljm}(h) = E\left[cc_{lm}(h)\right] + \eta_{ljm}, \tag{23}$$

where $cc_{lm}(h)$ denotes the function for claim cost of insuring an individual with health status $h$ with plan type $l$ in state $m$; and non-claim marginal cost is denoted by $\eta_{ljm}$. In (23), expectation is taken over a random error for individual's realized claims cost. An important feature of $cc_{lm}(h)$ is that it depend only on a plan type ($l$) and market ($m$), not on an insurer's identity ($j$). As discussed in the previous section about the Medigap market, this assumption is reasonable because all Medigap plans are standardized and because a Medigap enrollee does not receive medical care from a network of providers that are specific to an insurer. The need for the assumption will be discussed later in the section for identification.

Insurer $jm$'s profit from plan $l$ is given by:

$$\begin{aligned}\pi_{ljm} &= p_{ljm}Q_{ljm} - \int\limits_z mc_{ljm}(h)q_{ljm}(z)dF_z \\ &= (p_{ljm} - \eta_{ljm})Q_{ljm} - \int\limits_z E\left[cc_{lm}(h)\right]q_{ljm}(z)dF_z.\end{aligned}$$

An insurer $j$'s total profit in market $m$ is $\pi_{jm} = \sum_{l \in L_{jm}} \pi_{ljm}$. The optimal premium for each plan of an insurer must satisfy the first order condition as follows:

$$\frac{\partial \pi_{jm}}{\partial p_{ljm}} = Q_{ljm} + \sum_{l' \in L_{jm}} \left[(p_{ljm} - \eta_{ljm})\frac{\partial Q_{l'jm}}{\partial p_{l'jm}} - \int\limits_z E\left[cc_{lm}(h)\right]\frac{\partial q_{l'jm}(z)}{\partial p_{l'jm}}dF_z\right] = 0 \quad (24)$$

Note that because an individual's claims cost depends on the individual's health status $h$, an insurer's total profit will depend on the distribution of health statuses of enrollees in plans of the insurer. Then an insurer's optimal pricing decision will take into account how different levels of a premium affects the distribution of its enrollees' health statuses, which is captured by the the last term in equation (24).

Now I discuss the specification of marginal cost $mc_{ljm}(h)$. I assume that

$$cc_{lm}(h) = \exp\left(\gamma_m + \gamma_l + \sum_{n=1}^{2} \gamma_{h,n}\mathbf{1}[h = n]\right) + \nu. \tag{25}$$

The first and second term $\gamma_m$ and $\gamma_l$ denote market and plan type fixed effects. The market fixed effects capture differences in costs of medical care across different states. The plan type fixed effects account for differences in claims costs across different plan types. Each Medigap plan type has a different level of generosity as shown in Figure 2, and the plan type fixed effects will capture the differences in costs that result from the different levels of generosity. Medigap plan A is the least generous plan whereas Medigap plan J offers the most generous coverage including prescription drug benefits. If a plan offers more comprehensive coverage, then the plan will be financially responsible for a larger fraction of an individual's medical expenditures. Another possibility that can be captured by $\gamma_l$ is the moral hazard effect. Because an individual having a more comprehensive plan faces a lower out-of-pocket price for medical care, the individual would be more likely to utilize more medical care, raising the plan's cost. The third term captures differences in expected claims cost for individuals having different health statuses. Recall that $h$ takes on 1 and 2 when an individual's health status is excellent and good, respectively. The effect of poor health status on claims cost is normalized to zero.

Although $cc_{lm}(h)$ does not include an explicit interaction between health status and plan type, the effect of plan type on claims cost $cc_{lm}(h)$ is not independent of an individual's health status. Because $\gamma_l$ and $\gamma_{h,n}$ enter the exponential function in (25), the effect of $\gamma_l$ on $cc_{lm}(h)$ will depend on an individual's health status $h$, and the effect will be greater for individuals having health statuses with larger values of $\gamma_{h,n}$. This property of the model captures the possibility that claims cost of a more generous Medigap plan is greater for relatively unhealthy individuals. Because these individuals will incur more medical expenditures, and because a greater part of the expenditures is covered by a more generous plan, it is likely that a more generous plan is costlier for an insurer when enrolling a relatively unhealthy individual. Similarly, the effect of plan type will be greater in states having higher medical care costs, i.e., larger values of $\gamma_m$. That is, a more generous plan is costlier for an insurer in a state having a higher medical care cost.

Lastly, $\nu$ is a random shock to a realized claim that is i.i.d. across individuals and plans. I assume that $\nu$ is completely random so that an individual does not select on $\nu$ when making a decision. This assumption implies that

$$E[cc_{lm}(h)] = \exp\left(\gamma_m + \gamma_l + \sum_{n=1}^{2} \gamma_{h,n}\mathbf{1}[h=n]\right). \tag{26}$$

Then the first order condition (24) becomes:

$$\begin{aligned} Q_{ljm} \quad = \quad & \sum_{l' \in L_{jm}} \left[ \exp\left(\gamma_m + \gamma_l\right) \int\limits_z \exp\left(\sum_{n=1}^{2} \gamma_{h,n}\mathbf{1}[h=n]\right) \frac{\partial q_{l'jm}(z)}{\partial p_{l'jm}} dF_z \right] \\ & - \sum_{l' \in L_{jm}} (p_{ljm} - \eta_{ljm}) \frac{\partial Q_{l'jm}}{\partial p_{l'jm}} \end{aligned}$$

In the data, there are two different kinds of information about claims cost. First, the individual-level data (MCBS) provides information on claims cost for an individual having a Medigap plan.[55] Then I can calculate the conditional average of realized claims costs for individuals of health status $h'$ having any Medigap plan in the MCBS,

[55] Exactly, the MCBS provides information on how much an individual's supplemental plan covered the individual's medical expenditures in a given year.

$E[cc_i|h_i = h']$. The model is related to the data moment in the following way:

$$E[cc_i|h_i = h'] = \frac{\int_z \mathbf{1}[h = h'] \sum_{j \in J_m, l \in L_j} cc_{lm}(h) q_{ljm}(h) dF_z}{\int_z \mathbf{1}[h = h'] \sum_{j \in J_m, l \in L_j} q_{ljm}(h) dF_z} \tag{27}$$

Another kind of information about claims cost available in the data is information on each Medigap plan's average claims cost, $Acc_{lm}$. The prediction of the model on expected claims cost per enrollee in plan $ljm$ is:

$$\begin{aligned}
\widehat{Acc_{ljm}} &= \frac{\int_z E\left[cc_{lm}(h)\right] q_{ljm}(z) dF_z}{Q_{ljm}} \\
&= \exp\left(\gamma_m + \gamma_l\right) \frac{\int_z \exp\left(\sum_{n=1}^{2} \gamma_{h,n} 1[h = n]\right) q_{ljm}(z) dF_z}{Q_{ljm}} \qquad (28)
\end{aligned}$$

From (28), it is clear that the demand system indirectly determines $\widehat{Acc_{ljm}}$ by affecting the average health status of enrollees in plan $ljm$. In order to link model prediction $\widehat{Acc_{ljm}}$ to observed average claim costs in the data $Acc_{ljm}$, I assume that

$$\begin{aligned}
\ln\left(Acc_{ljm}\right) &= \ln\left(\widehat{Acc_{ljm}}\right) + \omega_{lm} \qquad (29) \\
&= \gamma_m + \gamma_l + H_{ljm}(q; \gamma_h) + \omega_{ljm}
\end{aligned}$$

where $H_{ljm}(q; \gamma_h) \equiv \ln\left(\frac{\int_z \exp\left(\sum_{n=1}^{2} \gamma_{h,n} 1[h=n]\right) q_{ljm}(z) dF_z}{Q_{ljm}}\right)$; and $\omega_{lm}$ is a random error that captures measurement errors or sampling errors due to a finite number of enrollees in each plan in the data. In equation 29, it is clear that once a market and plan type are controlled for, higher claims cost for a plan can be attributable to the third term, which measure the average health status of enrollees in a plan. This property of the model follows from the assumption that $cc_{lm}(h)$ does not depend on an insurer's identity, and I will exploit this property in identification.

# 4 Identification and Estimation

This section provides a discussion of estimation and identification of the model described above. The model will be estimated with generalized method of moments. In this section, I present a set of moment conditions and how each moment condition helps to identify parameters in the model. Then I discuss the estimation procedure in details.

## 4.1 Identification

**Claims Cost** I start with discussion of identification of parameters in the function ($\gamma s$) for claims cost in equation (26). Given the knowledge of $q_{ljm}(z)$, parameters $\gamma s$ are identified using two equations (27) and (29). The effect of health status on claims cost is identified by the moment condition (27), which provides information how much Medigap plans paid for individuals with a certain health status. The market and plan type fixed effects are identified by the following moment conditions constructed from equation (29): for any $m$ and $l$,

$$\begin{aligned} E[\omega_{ljm}|m] &= 0; \\ E[\omega_{ljm}|l] &= 0. \end{aligned}$$

**Mean Utility** Although search frictions are present in the model, an individual's choice probability in (19) is similar to the choice probability in standard random coefficient models of demand (e.g. Berry 1994; Berry et al. 1995). Given plan-level unobserved demand shock $\xi_{ljm}$ present in the model, I include the following moments for aggregate market share:

$$Q_{ljm} = \int_z q_{ljm}(z) dF_z \text{ for all } l, j, m. \tag{30}$$

Berry et al. (1995) show that given other parameters, there is a unique mean utility $\delta_{ljm}$ that exactly solves the system of nonlinear equations in (30). Mean utility $\delta_{ljm}$ is defined as the part of utility $u_{ljm}(z, \epsilon)$ that is independent of individual heterogeneity:

$$\delta_{ljm} = \sum_{l'=A}^{J} \beta_{l'} \mathbf{1}\left[l = l'\right] + \alpha_0 p_{ljm} + b_j + \mu_m + \xi_{ljm}.$$

In order to identify parameters in $\delta_{ljm}$, it is necessary to make a further assumption on a joint distribution of $\xi_{ljm}$ and observed variables in $\delta_{ljm}$. Usually a problem arises because $p_{ljm}$ is an endogenous choice of an insurer $j$, and because $\xi_{ljm}$ is known by the insurer when setting $p_{ljm}$. Therefore $\xi_{ljm}$ and $p_{ljm}$ are likely to be correlated, and an orthogonality condition between $p_{ljm}$ and $\xi_{ljm}$ will be violated. A usual solution for this problem is to use an instrument that is correlated with $p_{ljm}$ but not with $\xi_{ljm}$. In this paper, I use a strategy similar to Hausman (1996) and Nevo (2001), who use the average of prices charged by the same firm in other markets. The identifying assumption is that $\xi_{ljm}$ is independent of $\xi_{ljm'}$ and marginal cost shocks $\eta_{ljm'}$ in a market $m'$ that is different from $m$. Given this assumption, premiums of the same firm in other markets are valid instruments. Premiums of firm $j$ in two different markets $m$ and $m'$ will be correlated due to the common marginal cost, and $p_{ljm'}$ will be uncorrelated with $\xi_{ljm}$ due to the independence assumption. In the actual estimation, I use the average of $p_{ljm'}$ for all other markets $m'$ as an instrument. For other variables in $\delta_{ljm}$, I assume orthogonality between them and $\xi_{ljm}$. Because Medigap plans are exogenously standardized, the orthogonality condition between a dummy variable for each plan type $\mathbf{1}[l = l']$ and $\xi_{ljm}$ is likely to be valid. After all, I have the following moment conditions:

$$E[\xi_{ljm}|X_q] = 0 \tag{31}$$

where $X_q$ is a set of the aforementioned instruments including $\overline{p_{ljm}}$, the average premiums charged by the same insurer in other states, as well as plan types, dummy variables for insurers having distinct $b_j$ and dummy variables for each state.

**Overall Search Cost** There are two different groups of parameters related to search frictions. The first group of parameters are those that enter the search-cost distribution. These parameters determine the overall search cost for individuals and heterogeneity of search costs depending on individuals' characteristics. The second group of parameters are those that determine sampling probability $\rho_{jm}$. In this subsection, I will discuss identification of the first group of parameters given sampling probability of each Medigap insurer $\rho_{jm}$.

There are three different kinds of parameters that enter the search-cost distribution: a constant, coefficient for the Internet usage and coefficients for each health status. First, I discuss identification of the constant term, which determines the overall search cost for all individuals. In order to separately identify the constant from parameters in the utility function, I exploit the exclusion restriction that an individual's search cost only affects the individual's choice of an insurer, not the choice of a plan type within an insurer. Recall the alternative expression of an individual's demand for a Medigap plan in equation (22):

$$q_{ljm}(z) = q_{l|jm}(z) \times q_{jm}(z).$$

The first term is demand of individual having characteristic $z$ for plan type $l$ conditional on choosing insurer $jm$, which does not depend on the individual's search cost; and the second term is the individual's demand for insurer $jm$, which is affected by search cost. As discussed earlier, the exclusion restriction will create a wedge between substitution patterns across plan types within an insurer and substitution patterns across different insurers.

Thus, I construct the following moment conditions: denoting $\overline{p_{ljm}}$ as the instrument for a premium for plan $ljm$,

$$E[\xi_{ljm}\overline{p_{ljm}} \times \mathbf{1}[j = \text{United Healthcare}]] = 0; \tag{32}$$

$$E[\xi_{ljm}\overline{p_{ljm}} \times \mathbf{1}[j = \text{Blue Cross Blue Shield}]] = 0; \tag{33}$$

$$E[\xi_{ljm}\overline{p_{ljm}} \times \mathbf{1}[l = F]] = 0. \tag{34}$$

Moment conditions (32) and (33) are informative about consumers' substitution across plan types with respect to their premiums within each of the two largest Medigap insurance companies; and moment condition (34) is informative about consumers' substitution across plan Fs offered by different insurers. Here I consider plan Fs because they are the most popular Medigap plan type and are offered by almost all insurers. The constant in the search-cost distribution is identified by generating substitution patterns that satisfy these moment conditions.

**Individual Heterogeneity** Now I discuss identification of individual heterogeneity in search costs: the Internet usage and health status, and I also discuss identification of preference heterogeneity in the utility for a Medigap plan. An important difference between the two variables entering the search-cost distribution is that the former only affects the distribution whereas the latter enters both the distribution and utility for a Medigap plan. Similarly, an individual's income only affects the individual's preference for Medigap plans but does not have impacts on the individual's search cost. The variables entering either the utility or search-cost distribution can be identified with variation in observed Medigap choices across individuals having different characteristics. If an individual who uses the Internet is more likely to purchase a Medigap plan, then the only way the model can generate this pattern is by making the individual have lower search costs. Moreover, if an individual having a higher income is more likely to purchase a Medigap plans, then the model must make such an individual have less sensitive to a Medigap premium. Thus, I construct the following moment condition using the individual-level data (MCBS):

$$E\left[d_i - \sum_{j\in J_m, l\in L_m} q_{ljm}(z_i)\middle| X_{mcbs}\right] \;=\; 0, \tag{35}$$

where $d_i$ is an indicator variable that equals one when individual $i$ in the MCBS chooses any Medigap plan; $q_{ljm}(z_i)$ denotes individual $i$'s demand for plan $ljm$; and $X_{mcbs}$ is a set of individual characteristics. Moment condition (35) requires that the model predicts demand for any Medigap plan that matches observed Medigap purchase decisions for individuals having different characteristics.

However, this moment condition will not be sufficient to separately identify parameters for health statuses in the utility and search-cost distribution because an individual's observed choice of whether to buy any Medigap plan can be rationalized by either search cost or preference. Thus, I use another moment condition that is informative about search costs of individuals having different health statuses. I use a moment condition constructed from equation (29):

$$E[\omega_{ljm}|p_{ljm}] = 0 \tag{36}$$

where $p_{ljm}$ is a premium charged by plan $l$ of insurer $jm$. Given market and plan type fixed effects in (29) are pinned down by other moment conditions, moment condition (36) is informative about parameters that affect the third term $H_{ljm}(q;\gamma_h)$ in equation (29). Note that $H_{ljm}(q;\gamma_h)$ measures the average health status of enrollees in plan $l$ of insurer $jm$, which directly depends on demand of individuals having different health statuses for the plan. Then moment condition (36) will be informative about how demands of individuals having different health statuses are related to a plan's premium, thereby providing important information about substitution patterns of different individuals with respect to a premium. Such information will identify different search costs faced by individuals having different health statuses.

**Sampling Probability** Lastly, I discuss identification of parameters $\beta_x$ in equation (17) that determines sampling probability $\rho_{jm}$ in an individual's search process. The ideal dataset to identify parameter $\beta_x$ would provide information on an individual's choice set. However, such a dataset is hardly available for researchers. Therefore, identification of $\beta_x$ must rely on observed demand and claims cost for different plans. It is clear that the data on demand alone do not identify $\beta_x$ because variation in demand for different insurers can be rationalized by brand effects for large insurers or sampling probability. For example, United Healthcare has a large market share because consumers prefer the insurer or because the insurer has a high probability to be in consumers' choice set. Thus I augment the demand data with the data on the average claims cost for each plan. I supplement the following moment conditions constructed from equation (29):

$$E[\omega_{ljm}|x_{jm}] = 0 \tag{37}$$

where $x_{jm}$ is an insurer's characteristics in equation (17) for sampling probability. Similarly to the case for $p_{ljm}$, an insurer's characteristic $x_{jm}$ does not directly affect the insurer's claims cost but affects the cost only through the average health status of enrollees in the insurer's plan, $H_{ljm}(q; \gamma_h)$. Then moment condition (37) will be informative about substitution patterns of individuals having different health statuses with respect to an insurer characteristic $x_{jm}$.

In order to see how an insurer's sampling probability affects the substitution patterns of individuals with different health statuses, note that the effects of sampling probability on an individual's demand will be greater for individuals having large search costs. If an individual's search cost is low, then an insurer's sampling probability will not matter for the individual because searching would not be very costly for this individual. For an individual with larger search cost, in contrast, an insurer's sampling probability is likely to determine the individual's choice set because this individual will not search for other insurers outside an initial choice set. Then insurers with relatively large sampling probabilities are more likely to have individuals having higher search costs. If search cost is correlated with health status, then the average claims costs for plans of an insurer provide information about the average search cost of enrollees in the insurer and eventually information about the insurer's sampling probability. Then if search cost and health status are correlated, then moment condition (37) will provide information about substitution patterns of individuals having different search costs with respect to an insurer characteristic $x_{jm}$, thereby identifying $\beta_x$.

## 4.2 Estimation

The estimation proceeds in two steps. In the first step, I estimate the demand model and the process for claim costs (25) jointly with generalized method of moments, using moment conditions (31)–37. In the second step, I estimate each plan's non-claim marginal cost ($\eta_{ljm}$) using the first order condition for the optimal pricing (24).

In the first step, I solve for mean utility $\delta^*_{ljm}$ that satisfies the moment condition (20) for aggregate market share for each plan, using the nested fixed point algorithm in Berry et al. (1995). Let $G(\theta)$ be defined as a vector of moment conditions (31)–37, where $\theta$ is a vector parameters that enter the model for demand and claims cost. The criterion function for GMM is given by $\Psi(\theta) = G(\theta)'WG(\theta)$ where $W$ is a weighting matrix. Our estimation routine searches for $\theta$ that minimizes $\Psi(\theta)$. Evaluation of $G(\theta)$ can be broken into the following steps for each choice of $\theta$:

1. Given $\theta$, I solve for mean utility $\delta^*(\theta) = \{\delta^*_{ljm}(\theta)\}_{l,j,m}$ that satisfies the conditions for aggregate market shares (20), using the contraction mapping used in Berry et al. (1995).

2. With $\theta$ and $\delta^*(\theta)$, I calculate the demand $q_{ljm}(z)$ of an individual with characteristic $z$ using equation (19).

3. $G(\theta)$ is evaluated with $q_{ljm}(z)$.

Once I find estimates for $\theta$, I invert the first order condition for the optimal pricing (24) to recover non-claim marginal cost $\eta_{ljm}$ as in Berry et al. (1995). For the simple case that an insurer offers only one plan, inverting the equation (24) results in the following expression for $\eta_{ljm}$:

$$\eta_{ljm} \quad = \quad p_{ljm} + \frac{Q_{ljm} - \exp\left(\gamma_m + \gamma_l\right) \int_z \exp\left(\sum_{n=1}^{2} \gamma_{h,n} \mathbf{1}[h = n]\right) \frac{\partial q_{l'jm}(z)}{\partial p_{l'jm}} dF_z}{\frac{\partial Q_{l'jm}}{\partial p_{l'jm}}}. \quad (38)$$

Note that all parameters that enter the right-hand side of (38) are estimated in the first step.

# 5 Estimates

**Demand** Table 30 presents the estimates for the search cost distribution. If a consumer uses the Internet, then the consumer will have lower search costs; and individuals having excellent health status are more likely to have lower search costs compared to those with good and poor health. As mentioned in the model section, coefficients for health status in search costs distribution are supposed to capture a correlation between health and search costs that is not captured by the Internet variable alone. For example, Fang et al. (2008) find that an individual cognitive ability is a main source for advantageous selection into the Medigap market. Those with a lower cognitive ability are less likely to purchase a Medigap, and those with a decline in cognitive ability are very likely to be unhealthy.

In the bottom panel, I report simulated search costs distribution for each health status. The results show that the magnitude of search costs is large enough to affect an individual's demand for Medigap. The average search cost for overall population is \$832 in terms of 2003 dollars. This means that an individual is willing to forgo \$832 gains in utility by not searching. Given that an average premium for the most popular plan F is about \$1500, the average search cost is a very large fraction of the premium. This large magnitude of the average search cost results mainly from high search costs of individuals having good and poor health have high search costs. Relatively unhealthy individuals have high search costs for two reasons: First, they are less likely to use the Internet; and the second reason is because of the estimated coefficients for health status in the search-cost distribution.

Table 31 shows the estimates for parameters in the utility function. Conditional on other characteristics, consumers with good and poor health statuses will receive a higher utility from a Medigap plan compared to consumers with excellent health status. Moreover, individuals with a higher income are less sensitive to a premium. In Table 32, I report willingness to pay conditional on health status (but unconditional on other factors), which was calculated based on the estimates. The results show that unhealthy consumers are more willing to pay for Medigap plans. However, these consumers are less likely to purchase a Medigap plan because they face much higher search costs as shown in Table 30. These results are consistent with evidence for advantageous selection Fang et al. (2008) find for the Medigap market.

Table 33 presents estimates for brand preference and sampling probabilities for large insurers. The two largest national firms, United Healthcare and Blue Cross Blue Shield, have both higher brand preference and sampling probabilities. The results show that there are large variations in brand preference and sampling probability across insurers. Given the estimated sampling probabilities, it is possible to calculate a distribution of numbers of insurers in a choice set before searching, which is presented in Table 34. The results show that a typical consumer will have a initial choice set with a very small number of insurers. Combined with high search costs of the unhealthy, an initial choice set with a small number of firms will have a large impact on the unhealthy, which results in advantageous selection into the Medigap market.

Table 35 present elasticities calculated from the estimates. I calculated own-elasticity of demand with respect to a premium and cross-elasticity of demand with respect to a premium. Own-elasticity here is defined as a percentage change in demand for an insurer when the insurer increases its plans' premiums by one percent. In other words, own-elasticity measures the rate with which consumers substitute into other Medigap insurers or the outside option when an insurer raises premiums. Cross-elasticity here is defined as a percentage change in demand for an insurer when all other insurers increase premiums for all of their plans by one percent. In other words, cross-elasticity measures the rate with which consumers substitute into an insurer when from all other Medigap insurers raise premiums. The results show that cross-elasticities are much lower than own-elasticities in absolute values, which implies that a consumer is more likely to substitute into the outside option than into other Medigap insurers when an insurer raise premiums for its plans. The differences between the two elasticities reflect the fact that search frictions affect an individual's choice of an insurer, not plans within an insurer.

**Cost** Table 36 presents estimates for parameters in the function for claims cost in 26. The estimates show that costs of insuring individuals with Medigap plans A through G do not differ very much from each other. However, Medigap plans H, I and J cost more than other plans. The main difference between these plans and other plans is provision of prescription drug coverage, and the larger estimated cost for plans H,I and J implies that prescription drug coverage is a costly benefit for an insurer to offer. Table 36 also displays the estimates for coefficients for health statuses in the function for claim cost. The positive estimates for good and poor health status mean that individuals having such health statuses are costlier for an insurer to enroll than individuals having excellent health status. Moreover, the estimates show that individuals with poor health statuses are even costlier to insure than those with good health status. The estimates imply that costs of insuring individuals having good and poor health status are 1.8 and 5.1 times as expensive as insuring individuals having excellent health status, respectively. This means that the average health status of enrollees in a plan is an important determinant of the plan's cost, and an insurer's optimal pricing will eventually take into account how its strategy affects what kinds of individuals would enroll with the insurer.

# 6 Model Fit

In this section, I provide tables about model fits in order to show that the model can fit important features of the data. Here I discuss model fits only for the patterns in the data that are not perfectly fitted with structural error terms in the model. Recall that the aggregate market shares are perfectly fitted with unobserved heterogeneity term in the utility $\xi$, and that the observed premiums charged by insurers are perfectly fitted with non-claim marginal cost $\eta$.

Table 37 shows model fits for an individual's Medigap choice in the extensive margin. The data moments here are probabilities for an individual to purchase a Medigap plan conditional on the individual's characteristics. The results in the table show that the model is able to fit the pattern in the data that unhealthier individuals are less likely to purchase a Medigap. The data moments also show that individuals having higher incomes and using the Internet are more likely to purchase a Medigap plan. The model can also fit these patterns.

Another important feature in the data is a large difference in Medigap claims cost for individuals having different health statuses. Table 38 shows that the difference is very large between individuals having different health statuses, and that the model is able to fit the difference.

Lastly, Table 39 presents the pattern in the data on average claims costs for different plans and relevant model predictions. First, a very high correlation between average claims costs and premiums for Medigap plan Fs in the data. Although the model's prediction for this correlation is not perfect, the model is able to fit the overall pattern of the correlation. Note that the model does not have a parameter that would directly fits this pattern in the data. In other words, a premium does not directly enter a plan's claims-cost function. Instead, the model fits this pattern by making unhealthier individuals to select into Medigap plan Fs having higher premiums, raising costs of these plans. Given the feature of the model, I view that the model is able to fit the pattern in the data.

The other data moments in Table 39 are average claims costs for large insurers. I find that the model is able to fit the general pattern in the data on average claims cost. Similarly to the correlation between claims costs and premiums, the model also does not have parameters in an insurer's cost function that would fit these patterns in the data. One important assumption in the model is that the claims-cost structure is the same for all insurers due to standardization of Medigap plans. Therefore, the model fits the observed differences in average claims costs with demand of individuals with different health statuses for different insurers. The model can generate differential demand of individuals having different health statuses by making insurers have different sampling probabilities. As discussed earlier, insurers having higher sampling probabilities will differentially attract individuals having higher search costs, who tend to be unhealthier. Thus, the differences in insurers' sampling probabilities will play a crucial role in fitting the observed pattern in the data.

# 7 Counterfactual Analysis

In this section, I use the estimated model for counterfactual simulations. The purpose of counterfactuals is to understand the effects of search friction on an equilibrium and welfare. I assume that the government provides Medicare beneficiaries with information on available Medigap plans so that all consumers have full information about their choice set, even without searching. In order to understand an interaction between search frictions and adverse selection and its equilibrium effects, I simulate the model under two different cases. In the first case, I simulate the effects of policy on consumers' choices in a partial equilibrium, where I do not allow insurers to re-optimize their premiums in response to the policy. In the second case, I simulate let insurers re-optimize their premiums under the policy.

Table 40 presents results in a partial equilibrium. Because the only change in an environment for consumers is absence of search costs, a consumer's utility increases for everyone. Medigap takeup rates more than double, and an increase in the rates are greater for unhealthier consumers. Because search costs are larger for the unhealthy, their choice sets are likely to have only a few insurers with search frictions, which may not be always good options to purchase. With perfect information on available choices induced by the policy, they can choose any available plans, which will lead to a greater Medigap demand. As a result, the unhealthy are more likely to purchase Medigap after the policy. In other words, the policy induces adverse selection in the Medigap market, which originally exhibits advantageous selection. With respect to welfare, overall consumer's surplus more than doubles, compared to the baseline, and an increase in surplus is greater for unhealthier consumers.

Although the policy increases a consumer's surplus greatly for every consumer when premiums are fixed, it is not clear how the policy will affect the market outcomes when insurance companies can adjust their premiums. One one hand, the policy can still be beneficial. Because a reduction in search frictions will make demand more elastic with respect to premiums, insurers will have an incentive to reduce their premiums, which in turn will increases a consumer's utility even more. On the other hand, an increase in the extent of adverse selection induced by the policy can increase a premium and reduce consumer's welfare.

The results are presented in Table 41. I find that although overall welfare increases, healthy individuals are worse off with the policy. Because insurance companies increase premiums, many healthy individual, who had low search costs in the first place, are paying a higher premium without much benefit from the policy. Overall Medigap takeup rates increase compared to the baseline, but an increase in the rates is not as great as in a partial equilibrium; and takeup rates for healthy individuals decrease due to an increase in premiums.

Why do premiums increase when firms can adjust them? There are two possible channels in the model. The first obvious one is through the extensive margin. Because more unhealthy individuals now purchasing Medigap, average claim costs for each plan will increase, which leads to a higher premium. The second channel is more subtle and through the intensive margin. Starc (2012), who studies imperfect competition and adverse selection in Medigap, find that an increase in a premium leads to a higher cost of claims because unhealthier individuals are less sensitive to premiums, and healthier consumers are driven away by a higher premium. As a result, the substitution patterns lower markups of insurance companies. In this paper, an unhealthy individual's high search costs generate the substitution patterns in demand and lowers markups in the baseline. With the policy that give more information, the unhealthy individuals are not insensitive to a premium any longer. Then an increase in premiums will no longer lead to an increase in claims, which will give firms even more incentives to increase their markups and thereby premiums.

# 8 Conclusion

In this paper, I study how consumer search frictions affect adverse selection and competition in the Medigap market. I find that search frictions are significant and their effects on consumers are heterogeneous, depending on health risks of consumers.

Relative healthy individuals forgo about 16% of an average premium due to search frictions, whereas unhealthy individuals forgo about an amount as large as an average premium. As a result, the Medigap market exhibits advantageous selection. That is, the unhealthy are more likely than healthier individuals to skip purchasing a Medigap plan even though the estimates suggest that they have a higher willingness to pay for Medigap coverage. Although search frictions give firms an incentive to raise premiums by making demand inelastic, high search costs of the unhealthy lower a premium. When the government provides more information on available options to reduce search frictions, I find that although many individuals benefit from the policy, adverse selection is induced, which makes healthy individuals worse off. From this finding, I argue that efforts to increase access to information on available choices should be accompanied by a policy that reduces the extent of adverse selection.

# Appendix to Chapter 1

## A 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:

$$Prob(y > 0|x) = \frac{\exp(x\beta_1)}{1 + \exp(x\beta_1)}. \tag{39}$$

$y$ 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 $\beta_1$ 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 $\beta$ and $\gamma$ 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 $\epsilon$ is normally distributed. The first set of moments will pin down $\beta_2$, and the second set of moments will pin down $\gamma$. The estimates are presented in Table 22.

Note that we make an implicit assumption here that $\epsilon$ is independent of the logistic error term for equation (39). 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 $\epsilon$ is a purely random shock to claims costs, and individuals do not select on $\epsilon$ 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:

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

# B 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.

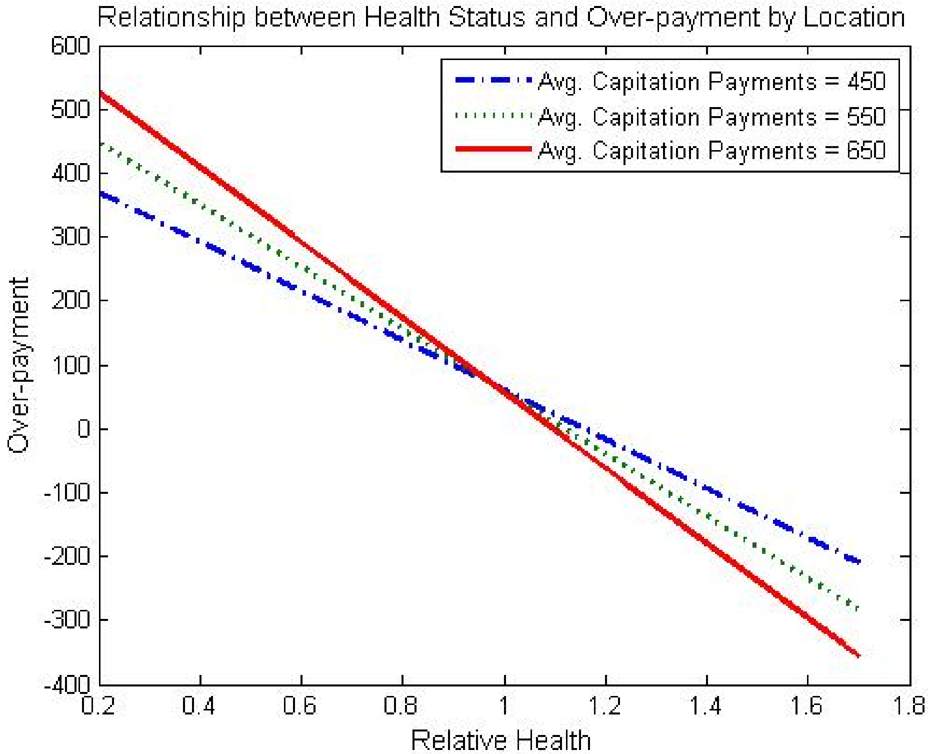
# C Figures and Tables

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

| | County-years | | |
|---|---|---|---|
| | No Ad | Ad < \$250k | Ad≥\$250k |
| No. of county-year | 800 | 1264 | 385 |
| Population (age ≥ 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 |
| Market Shares for Firms w/ ad < mean | 0.05 | 0.08 | 0.06 |
| Market Shares for Firms w/ ad > mean | n/a | 0.12 | 0.11 |
| Total Number of Insurer-county-year | 893 | 2648 | 1440 |

Note: 'County-years with No Ad' means county-years belonging to a local advertising market having no advertising spending; 'County-years with Ad < \$250k' means county-years belonging to a local advertising market where total advertising spending is below \$250,000; and 'County-years with Ad ≥ \$250k' means county-years 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 | | County-years No ad | Ad < \$250k | 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: 'County-years with No Ad' means county-years belonging to a local advertising market having no advertising spending; 'County-years with Ad < \$250k' means county-years belonging to a local advertising market where total advertising spending is below \$250,000; and 'County-years with Ad ≥ \$250k' means county-years belonging to a local advertising market where total advertising spending is at least \$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 in a County | -1.012*** | (0.0278) |
| Avg Capitation Payment in a County | 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 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 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 9: Estimates for Key Parameters in Utility

| Variables | Estimates | Std. Err. |
|---|---|---|
| Ad effects ($\phi_0$) | 0.040 | (0.063) |
| $\log(rh_i)$ ×Ad effects ($\phi_1$) | -0.036** | (0.018) |
| Curvature of Ad effects ($\phi_2$) | 0.012** | (0.005) |
| $\log(rh_i)$ ×Outside option (part of $\lambda$) | 0.233** | (0.097) |
| Premium ($\alpha_0$) | -0.002*** | (0.0005) |
| $\log(rh_i)$ ×Premium ($\alpha_1$) | 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 ($\delta_{jmt}$)

| 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 $\zeta$ ($\sigma_\xi$) | 1.356*** | (0.579) |
| Year Dummy | Yes | |

Table 15: Ban on Advertising

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

# Appendix to Chapter 2

## D Proof for Choice Probability

In this section, I prove how to derive an individual's expected demand for plan $ljm$. I will define the integral of the first and second term of $d_{ljm}(z, s, \epsilon, c)$ in equation (18) as follows:

$$\begin{aligned} q^1_{ljm}(z, c, s) &= \int_\epsilon d^1_{ljm}(z, s, \epsilon, c) dF_\epsilon \\ q^2_{ljm}(z, c, s) &= \int_\epsilon d^2_{ljm}(z, s, \epsilon, c) dF_\epsilon \end{aligned}$$

where

$$\begin{aligned} d^1_{ljm}(z, s, \epsilon, c) &\equiv \mathbf{1}\left[jm \in s\right] \mathbf{1}[r_m(s, z, \epsilon) < c] \mathbf{1}[u_{ljm}(z, \epsilon) = v_m(s, z, \epsilon)]; \\ d^2_{ljm}(z, s, \epsilon, c) &\equiv \mathbf{1}\left[jm \notin s\right] \mathbf{1}[r_m(s, z, \epsilon) \geq c] \mathbf{1}[u_{ljm}(z, \epsilon) = V_m(z, \epsilon)]. \end{aligned}$$

Note that:

$$\mathbf{1}[r_m(s, z, \epsilon) < c] = \mathbf{1}[V_m(z, \epsilon) - v_m(s, z, \epsilon) < c].$$

Then, by letting $\tilde{u}_{ljm}(z) \equiv u_{ljm}(z, \epsilon) - \epsilon_{ljm}$,

$$\begin{aligned} d^1_{ljm}(z, s, \epsilon, c) &= \mathbf{1}\left[jm \in s\right] \prod_{j' \in s} \left( \prod_{l' \in L_{j'}} \mathbf{1}[\tilde{u}_{ljm}(z) + \epsilon_{ljm} \geq \tilde{u}_{l'j'm}(z) + \epsilon_{l'j'm}] \right) \\ &\times \prod_{j'' \notin s} \left( \prod_{l'' \in L_{j''}} \mathbf{1}[\tilde{u}_{ljm}(z) + \epsilon_{ljm} \geq \tilde{u}_{l''j''m}(z) - c + \epsilon_{l''j''m}] \right). \end{aligned}$$

Using a property of type I extreme value distribution, I can calculate $q^1_{ljm}(z,c,s)$:

$$q^1_{ljm}(z,c,s) \quad = \quad \frac{\exp(\tilde{u}_{ljm}(z))\mathbf{1}\left[jm \in s\right]}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm \notin s\right]\right)}.$$

Similarly for $d^2_{ljm}(z,s,\epsilon,c)$, it can be shown that

$$\begin{aligned} d^2_{ljm}(z,s,\epsilon,c) \quad &= \quad \mathbf{1}\left[jm \notin s\right]\prod_{j'\in s}\left(\prod_{l'\in L_{j'}}\mathbf{1}[\tilde{u}_{ljm}(z)-c+\epsilon_{ljm} \geq \tilde{u}_{l'j'm}(z)+\epsilon_{l'j'm}]\right) \\ &\times \quad \prod_{j''\notin s}\left(\prod_{l''\in L_{j''}}\mathbf{1}[\tilde{u}_{ljm}(z)-c+\epsilon_{ljm} \geq \tilde{u}_{l''j''m}(z)-c+\epsilon_{l''j''m}]\right) \end{aligned}$$

Then

$$q^2_{ljm}(z,c,s) = \frac{\exp(\tilde{u}_{ljm}(z)-c)\mathbf{1}\left[jm \notin s\right]}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm \notin s\right]\right)},$$

and consumer $z$'s expected demand for plan $ljm$ is

$$\begin{aligned} q_{ljm}(z) \quad &= \quad \sum_{s\in S_m} Pr(s)\int_c\int_\epsilon d_{ljm}(z,s,\epsilon,c)dF_\epsilon dF_{sc|z} \\ &= \quad \sum_{s\in S_m} Pr(s)\int_c \frac{\exp\left(\tilde{u}_{ljm}(z)-c\mathbf{1}\left[jm \notin s\right]\right)}{1+\sum_{j'\in J_m}\exp\left(\tilde{u}_{lj'm}(z)-c\mathbf{1}\left[j'm \notin s\right]\right)}dF_{sc|z}. \end{aligned}$$

# E Figures and Table

Figure 2: Medigap Benefits

| | Plan Letter | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H | I | J |
| *Basic Benefits* | | | | | | | | | | |
| Medicare Part A Coinsurance and Hospital Benefits | | | | | | | | | | |
| Medicare Part B Coinsurance or Copayment | | | | | *(all plans must cover)* | | | | | |
| Blood (three pints per year) | | | | | | | | | | |
| *Extra Benefits* | | | | | | | | | | |
| Skilled Nursing Facility Coinsurance | | | X | X | X | X | X | X | X | X |
| Medicare Part A Deductible | | X | X | X | X | X | X | X | X | X |
| Medicare Part B Deductible | | | X | | | X | | | | X |
| Medicare Part B Excess Charges | | | | | | X | X | | X | X |
| Foreign Travel Emergency | | | X | X | X | X | X | X | X | X |
| At-Home Recovery | | | | X | | | X | | X | X |
| Prescription Drugs | | | | | | | | X | X | X |
| Medicare-Covered Preventive Services | | | | | X | | | | | X |

Table 23: Medigap Market Concentration

| Statistics | Market Share of the Largest Insurer in a State |
|---|---|
| Average | 0.506 |
| Standard Deviation | 0.165 |
| Maximum | 0.201 |
| Minimum | 0.835 |
| Number of States | 25 |

Source: National Association of Insurance Commissioners 2005.

Table 24: Plan C in PA

| Company | Premium | Average Claim Costs | Market Shares |
|---|---|---|---|
| Blue Cross Blue Shield | 1332.2 | 823.13 | 0.6231 |
| United Healthcare Ins Co (AARP) | 1553 | 1242.32 | 0.2647 |
| American Progressive L&H Ins of NY | 1588.5 | 1157.91 | 0.0601 |
| State Farm Mut Auto Ins Co | 1524.4 | 1241.84 | 0.0210 |
| Continental Life Ins Co Brentwood | 1317.8 | 928.98 | 0.0135 |
| United Teacher Assoc Ins Co | 1513.6 | 1066.55 | 0.0040 |
| Constitution Life Ins Co | 1859.3 | 1139.83 | 0.0034 |
| Bankers Fidelity Life Ins Co | 2165.5 | 1457.27 | 0.0020 |
| Central States H & L Co Of Omaha | 1662.5 | 966.56 | 0.0013 |
| United American Ins Co | 2388 | 1356.99 | 0.0013 |

Source: Weiss Rating 2003; National Association of Insurance Commissioners 2005.

Table 25: Descriptive Statistics for Medigap Plans

| Plan Types | Market Shares | Average Annual Premium | Average Annual Claim |
|---|---|---|---|
| A | .031 | 1005.9 | 1031.1 |
| B | .039 | 1412.4 | 1141.2 |
| C | .174 | 1482.7 | 1236 |
| D | .065 | 1291.8 | 1004.8 |
| E | .031 | 1297.6 | 989 |
| F | .478 | 1469.5 | 1109.7 |
| G | .06 | 1233.3 | 947.8 |
| H | .019 | 2073.8 | 1820.5 |
| I | .032 | 2151.6 | 1629.8 |
| J | .072 | 2537.1 | 2081.1 |

Source: Weiss Rating 2003; National Association of Insurance Commissioners 2005.

Table 26: Descriptive Statistics from the MCBS

| | Medigap Enrollees | | Non-Enrollees | | Overall | |
|---|---|---|---|---|---|---|
| % Medigap | 1 | | 0 | | .247 | (.431) |
| % Health Status: Excellent | .560 | (.499) | .507 | (.500) | .520 | (.500) |
| % Health Status: Good | .29 | (.460) | .314 | (.466) | .308 | (.464) |
| % Health Status: Poor | .15 | (.373) | .178 | (.394) | .171 | (.389) |
| Income ($) | 37,533 | (28990) | 35,186 | (25751) | 35,756 | (26,604) |
| % Internet | .583 | (.494) | .498 | (.500) | .519 | (.500) |
| N | 1,037 | | 3,147 | | 4,184 | |

Note: Standard errors are in parentheses.
Source: Medicare Current Beneficiary Survey 2003—2005.

Table 27: Correlation Coefficient between Health Status and Internet Usage

| | Internet Use | |
|---|---|---|
| | No | Yes |
| Health Status: Excellent | .418 | .619 |
| Health Status: Good | .350 | .253 |
| Health Status: Poor | .231 | .129 |
| N | 2,088 | |

Source: Medicare Current Beneficiary Survey 2003—2005.

Table 28: Linear Probability Model for Medigap Choice

| VARIABLES | Estimates |
|---|---|
| Health Status: Good | 0.0148 |
| | (0.0128) |
| Health Status: Poor | 0.0178 |
| | (0.0158) |
| Income | 4.74e-07 |
| | (2.53e-07) |
| Internet Access | 0.0727 |
| | (0.0223) |
| Constant | 0.367 |
| | (0.0466) |
| Observations | 2,088 |
| R-squared | 0.224 |

Note: Dependent variable = whether an individual purchased a Medigap plan; State-fixed effects are included in the regression; The coefficient for excellent health status is normalized to zero.
Source: Medicare Current Beneficiary Survey 2003—2005.

Table 29: Relationship between Average Claims Cost and Premium

| Dependent Variable = Average Claim Cost of a Plan | |
|---|---|
| VARIABLES | Premium |
| Premium | 0.703 (0.079) |
| Brand Fixed Effect | Yes |
| State - Plan Type Fixed Effect | Yes |
| R-squared | 0.3481 |
| No. of Observations | 1,330 |

Source: Weiss Rating 2003; National Association of Insurance Commissioners 2005.

Table 30: Estimates for Search Cost

| Parameter Estimates | | | |
|---|---|---|---|
| Constant | Internet | Health: good | Health: poor |
| 4.54 | -3.62 | 4.07 | 3.94 |
| (1.21) | (0.95) | (1.32) | (1.01) |

| Average Search Costs in 2003 Dollars | | | | |
|---|---|---|---|---|
| | Overall | Excellent | Good | Poor |
| Baseline ($) | 832 | 249 | 1415 | 1569 |
| Internet = 1 ($) | 590 | 105 | 1078 | 1198 |

Note: 'Internet = 1' refers to individuals using the Internet.

Table 31: Utility Estimates

| Variables | Estimates | Std. Err. |
|---|---|---|
| Plan C | 4.16 | (0.88) |
| Plan F | 6.90 | (1.86) |
| Plan J | 11.80 | (2.03) |
| Premium | -.0035 | (.0006) |
| Income × Premium | 6.8e-6 | (2.2e-6) |
| Health Status: Excellent × Medigap | 0 (normalized) | |
| Health Status: Good× Medigap | 1.09 | (0.394) |
| Health Status: Poor× Medigap | 1.04 | (0.372) |

Note: Estimates for coefficients for Medigap plans other than C, F and J are not reported here.

Table 32: Medigap Demand and Willingness to Pay by Health Status

| | Medigap Demand | WTP for Plan F | WTP for Plan J |
|---|---|---|---|
| Overall | 0.210 | $1,791 | $2,667 |
| Health Status: Excellent | 0.221 | $1,656 | $2,476 |
| Health Status: Good | 0.204 | $1,953 | $2,895 |
| Health Status: Poor | 0.193 | $1,915 | $2,846 |

Note: WTP = willingness to pay; The average premiums for Plan F and J are $1,450 and $2,542, respectively.

Table 33: Estimates for Brand Effects and Sampling Probability

| Insurer | Brand Effects ($) | Sampling Probability |
|---|---|---|
| United Healthcare | $262 | 24.6% |
| Blue Cross Blue Shield | $451 | 36.1% |
| Mutual of Omaha | $73 | 5.0% |
| Banker's Insurance | -$130 | 8.8% |
| State Farm | $10 | 14.6% |
| United American | $336 | 16.0% |

Note: Estimates for brand effects in utility was converted to a unit of 2003 dollars; An insurer's sampling probability reported in the table is the average of the insurer's sampling probabilities across states it operate in.

Table 34: Distribution of Numbers of Insurers in an Initial Choice Set

| Number of Insurers | Probability |
|---|---|
| 0 | 0.286 |
| 1 | 0.402 |
| 2 | 0.225 |
| 3 and more | 0.086 |

Note: The numbers reported here is calculated using the estimated model. The probability that an individual does not meet with any insurer without searching is 28.6%; the probabilities that an individual meets with one and two insurers without searching is 40.2% and 22.5%, respectively; and the probability that an individual have three or more insurers in a choice set without searching is 8.6%.

Table 35: Elasticity

| Own-elasticity with respect to price | | | |
|---|---|---|---|
| Overall | Excellent | Good | Poor |
| -4.83 | -4.69 | -5.01 | -4.98 |

| Cross-elasticity with respect to price of other insurers | | | |
|---|---|---|---|
| Overall | Excellent | Good | Poor |
| 1.12 | 1.14 | 1.09 | 1.08 |

Table 36: Estimates for Claims Cost

| | Estimates | Std. Err. |
|---|---|---|
| Plan A | 0.048 | (0.072) |
| Plan B | 0.036 | (0.075) |
| Plan C | 0.122 | (0.072) |
| Plan D | -0.061 | (0.077) |
| Plan E | -0.119 | (0.078) |
| Plan F | 0 (normalization) | |
| Plan G | -0.119 | (0.078) |
| Plan I | 0.415 | (0.090) |
| Plan H | 0.243 | (0.089) |
| Plan J | 0.527 | (0.087) |
| Health Status: excellent | 0 (normalization) | |
| Health Status: good | 0.595 | (0.123) |
| Health Status: poor | 1.162 | (0.243) |

Table 37: Model Fit: Medigap Takeup Probability

| | | Data | Model |
|---|---|---|---|
| Health | Excellent | 0.248 | 0.247 |
| | Good | 0.217 | 0.213 |
| | Poor | 0.208 | 0.199 |
| Income | Below Median | 0.219 | 0.203 |
| | Above Median | 0.244 | 0.263 |
| Internet Usage | No | 0.194 | 0.194 |
| | Yes | 0.267 | 0.269 |

Note: The data moments is the probabilities to purchase any Medigap plan conditional on an individual characteristic.
Source: Medicare Current Beneficiary Survey 2003–2005.

Table 38: Model Fit: Medigap Claims Cost by Health Status

| | Data | Model |
|---|---|---|
| Health Status: Excellent ($) | 667 | 657 |
| Health Status: Good ($) | 1207 | 1183 |
| Health Status: Poor ($) | 3239 | 3212 |

Note: The data moment is the averages of Medigap claims cost conditional on health status.
Source: Medicare Current Beneficiary Survey 2003–2005.

Table 39: Model Fit: Aggregate Claims Cost

| | Data | Model |
|---|---|---|
| Corr. Coeff. with Premium of Plan F | 0.438 | 0.364 |
| United Healthcare | 1226 | 1230 |
| Blue Cross Blue Shield | 1267 | 1173 |
| Mutual of Omaha | 965 | 1002 |
| Banker's Life Insurance | 1112 | 962 |
| State Farm | 1048 | 1094 |
| United American | 1083 | 1171 |

Note: The correlation coefficient with premium of plan F refers to the correlation coefficient between average claims cost and premium for each plan. Other data moments are the averages of claims cost for each insurance company.
Source: Weiss Ratings 2003; NAIC 2005.

Table 40: Information Provision in a Partial Equilibrium

| | | Baseline | Information Provision |
|---|---|---|---|
| Medigap takeup (%) | Overall | 0.210 | 0.524 |
| | Health: Excellent | 0.221 | 0.457 |
| | Health: Good | 0.204 | 0.560 |
| | Health: Poor | 0.193 | 0.659 |
| Consumer's Surplus ($) | Overall | 88 | 233 |
| | Health: Excellent | 88 | 190 |
| | Health: Good | 91 | 254 |
| | Health: Poor | 83 | 324 |

Note: Consumer's surplus is measured in terms of 2003 dollars.

Table 41: Information Provision in a Equilibrium Model

| | | Baseline | Information Provision |
|---|---|---|---|
| Medigap takeup(%) | Overall | 0.210 | 0.225 |
| | Health: Excellent | 0.221 | 0.165 |
| | Health: Good | 0.204 | 0.294 |
| | Health: Poor | 0.193 | 0.278 |
| Premium Paid ($) | Medigap Plan F | 1538 | 1798 |
| | Medigap Plan J | 2552 | 2904 |
| Claim Costs ($) | Medigap Plan F | 1174 | 1424 |
| | Medigap Plan J | 2314 | 2648 |
| Consumer's surplus ($) | Overall | 88 | 94 |
| | Health: Excellent | 88 | 63 |
| | Health: Good | 91 | 130 |
| | Health: Poor | 83 | 118 |
| Industry Profits ($) | Overall | 63 | 69 |
| Social Surplus ($) | Overall | 151 | 164 |

Note: Consumer's surplus, industry profits and social surplus are measured in terms of 2003 dollars.

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