Advertising and Risk Selection in Health Insurance Markets*

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Abstract

We study impacts of advertising as a channel of risk selection in Medicare Advantage. We show evidence that both mass and direct mail advertising are targeted to achieve risk selection. We develop and estimate an equilibrium model of Medicare Advantage with advertising to understand its equilibrium impacts. We find that advertising attracts the healthy more than the unhealthy. Moreover, shutting down advertising increases premiums by up to 40% for insurers that advertised by worsening their risk pools, which further reduces the demand of the unhealthy. We argue that risk selection may make consumers better off by improving insurers' risk pools.

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1 Introduction

Many Americans purchase health insurance in private markets that are largely designed by the government. These markets, including Medicare Advantage, Medicare Part D, and health insurance marketplaces, have substantially expanded over time.[1] One of the important goals for the government in designing these markets is to provide access to health insurance to unhealthy individuals by mitigating insurers' risk selection (or cream-skimming), the selective enrollment of low-cost healthy individuals. In these markets, private insurers are prohibited from discriminating individuals based on their health risks in term of plan offering, premiums or plan benefits. Moreover, the government uses risk adjustment, through which insurers receives a subsidy based on an enrollee's health risk. However, the risk adjustment is still not perfect in practice, and the incentives for risk selection still remain.

Previous empirical studies find the presence of risk selection (Kuziemko et al., 2013) and discuss how the imperfect risk adjustment system leads to an excess government expenditure by providing excessive subsidies to insurers for enrolling low-cost healthy consumers (Brown et al., 2014). However, in evaluating risk selection, little is known about its effectiveness and its effects on equilibrium outcomes. By treating the demands of individuals with different health risks differently, risk selection affects an insurer's risk pool and thereby its marginal cost. Thus, with imperfect risk adjustment, risk selection will eventually affect an insurer's pricing. If risk selection decreases the premium, then it may rather help unhealthy individuals purchase health insurance and improve their welfare. Of course, overall welfare impacts depend on the possibility of excessive spending on risk selection (i.e., rent-seeking) due to insurers' competition for attracting the healthy individuals. The quantitative significance of these issues has not been studied in the existing literature, as the presence of risk selection is examined without using measures of risk selection tools.

In this paper, we empirically study advertising as a means of risk selection in the context of Medicare Advantage (MA), which offers an option for Medicare beneficiaries to choose private coverage instead of public traditional Medicare. Advertising can

[1] In 2014, roughly 16 million elderly individuals eligible for public insurance Medicare (Medicare beneficiaries) were insured by private Medicare Advantage plans. Medicare Part D provides prescription drug coverage to 37 million Medicare beneficiaries only through private plans. Health insurance marketplaces were introduced in 2014 due to the Affordable Care Act.

lead to risk selection through its asymmetric impacts on consumer demand depending on health status. A possible mechanism is a consumer's heterogeneous response to advertising. Unhealthy individuals may have problems with vision and hearing, which make it difficult for them to gather information from advertising. Similarly, unhealthy older individuals are more likely to have problems with cognitive abilities (see Fang et al., 2008), which can lead to a heterogeneous response to advertising. Another mechanism is sophisticated targeting by insurers. They may design advertising contents or choose the timing of advertising to target healthy individuals (See e.g., Neuman et al. 1998; Mehrotra et al. 2006). Moreover, they use not only mass advertising but also direct mailing to certain individuals.

We view advertising can play an important role of risk selection in health insurance markets. The significance of marketing activities and advertising by insurers in the health insurance markets was pointed out in the literature (see, e.g., Cebul et al., 2011). Furthermore, advertising in MA is largely unregulated, unlike the design of plan benefits. Thus, advertising can be much more responsive to the risk adjustment system. In this paper, we provide the first empirical analysis of equilibrium impacts of advertising on a health insurance market by focusing on its role as risk selection. We start our analysis by investigating whether MA insurers target advertising to individuals and regions where risk selection results in greater profits. Then we structurally estimate a model of the MA market and quantify the effects of risk selection through advertising on the market outcomes in MA such as demand, pricing, and government expenditures.

The MA market is an ideal environment in which to study risk selection for three reasons. First, an MA plan receives a subsidy called a capitation payment from the government for an enrollee and then bears the health care costs incurred by the enrollee. Although an MA plan often charges a premium, the capitation payment accounts for most of a plan's revenue. Moreover, the capitation payment has been known to be imperfectly adjusted to an enrollee's health risk. Therefore, concerns for risk selection in MA have arisen.[2] Second, as we describe in section 2, there is variation in the capitation payment across markets and over years, which allows us to identify how the incentive of advertising responds to changes in capitation payments and its quantitative

[2]Note that the government has allowed capitation payments to become more risk adjusted in the past 10 years. See Newhouse et al. (2012).

significance on market outcomes. Lastly, the large size of the MA program makes it a very important market to study.

We begin our empirical analysis by providing evidence that mass advertising is geographically targeted to markets where risk selection will be more profitable, exploiting policy variations in the data. We obtain the data for mass advertising by insurers from 2001 to 2007 from the AdSpender Database of Kantar Media, which includes advertising expenditures on TV, newspaper, radio, etc. In 2004, there are important changes in risk adjustment system of MA so that capitation payments are more adjusted based on an individual's risk score, which is constructed based on various measures of past health outcomes. An important feature of this policy is that risk score information is not used for calculating capitation payments for enrollees who are new to Medicare system, typically age 65 and 66. Therefore, one may expect that the gain from risk selection may depend more on size of new Medicare beneficiaries. By exploiting cross market and across time variations, we show that there are more advertising in markets with more new to Medicare population after 2004. Therefore, geographical targeting of advertising is related to the profitability of risk selection.

In order to understand the asymmetric impact of advertising on consumer demand with different health statuses, it is essential to control for other possible characteristics of insurers which may affect consumer demand. By following the spirit of Berry et al. (1995, 2004), we develop and structurally estimate a consumer demand model of MA markets with advertising. Consumers make a discrete choice to enroll with one of the available MA insurers or to select traditional Medicare. The impact of advertising can differ according to the consumer's characteristics, including the previous insurer choice and health status, which captures the possibility that different individuals respond differently to advertising. Consumer preferences for an insurer depend on characteristics such as premiums and coverage benefits. We also allow that the consumer can face the switching cost associated with changing insurance choices, which is known to be important in the context of MA (see Miller (2014), Miller et al. (2014), and Nosal (2012)).[3]

We estimate the demand side using data on consumer characteristics and choice from the Medicare Current Beneficiary Survey and data on insurer characteristics from

[3]For works on switching cost or inertia in other health insurance markets, see Handel (2013), Ho et al. (2015), and Polyakova (2014).

CMS State-County-Plan (SCP) files. Estimation is by generalized method of moments, in the spirit of Berry et al. (2004). We allow for insurer-year fixed effects and county fixed effects and use instrumental variables to account for the endogeneity of premiums and advertising stemming from unobserved plan heterogeneity. Our estimates show that healthier individuals are responsive to advertising, and thus, additional advertising attracts more healthy individuals. Moreover, sizable switching costs are associated with changing insurers. Because of the large switching costs, advertising has greater effects on the demand by new Medicare beneficiaries who face no switching costs. We also show evidence that a source of asymmetric impact of advertising on consumer demand is likely to be a heterogeneous consumer response instead of insurer sophisticated targeting.

We evaluate the importance of risk selection through advertising on consumer demand, pricing, and government expenditures by conducting a counterfactual experiment that exogenously shuts down the advertising activities. In order to investigate the supply side responses, we estimate the supply side parameters by assuming that firms play Bertrand Nash price competition in a differentiated goods market.[4] An insurer's revenue from an enrollee equals the sum of the premium and capitation payment for the enrollee. The capitation payment is adjusted based on individual characteristics, but importantly, it is not perfectly adjusted based on individual health risks, making the insurer's profit from an enrollee vary by individual. Thus, the optimal pricing takes into account the effects of these choices on the plan's composition of health risks.

We investigate the impact of shutting down advertising in two counterfactual situations. In one, premiums are exogenously fixed at their baseline levels, and in the other, insurers reoptimize their premiums in a situation without any advertising. We find that shutting down advertising lowers the overall demand for MA and that its impact is much larger for healthier consumers and new Medicare beneficiaries. Interestingly, when insurers reoptimize their premiums, the demand for MA decreases much more than when premiums are fixed exogenously. The decrease is especially pronounced, around 10%, for individuals that newly became eligible for Medicare because they do not have switching costs. The further decline is driven by a sharp increase in premiums, around 40%, among insurers that had relatively large advertising expenditures.

[4]Because we conduct a counterfactual experiment that exogenously shuts down advertising, we are agnostic about how advertising is optimally chosen in the economy with advertising.

The key mechanism is that shutting down advertising makes the insurers unable to engage in risk selection. As fewer healthier individuals will now obtain coverage through MA, the insurers' risk pools will deteriorate. With imperfectly risk-adjusted capitation payments, the change in the risk pool will increase premiums for those insurers. At the same time, premiums decrease for other insurers that had few or zero advertising expenditures, which highlights a rent-seeking aspect of risk selection: advertising improves an insurer's own risk pool while it negatively affects other insurers' risk pools. Overall, shutting down advertising increases premiums on average and decreases the demand. Moreover, a wasteful advertising competition through insurers' rent-seeking was likely to be limited as most small insurers did not advertise. Thus, under an imperfect risk adjustment system, risk selection through advertising may make consumers better off by lowering premiums without much inefficient spending. Although it is commonly discussed that risk selection should be minimized, our finding suggests that risk selection can possibly improve the welfare.

Related Literature This paper contributes to large literature empirically investigating selections in insurance markets. Although the majority of the literature focus on the consumer side selection, there are a few studies investigating risk selection by insurers.[5] Bauhoff (2012) studies risk selection in the German health insurance market by looking at how insurers respond differently to insurance applications from regions with different profitability levels. 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. Brown et al. (2014) provide evidence that insurers engage in risk selection in MA by exploiting changes in MA risk adjustment system.[6] 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 and its equilibrium impact.[7]

This paper is also related to new and growing literature studying supply-side com-

[5]See Chiappori and Salanie (2000), Finkelstein and McGarry (2006), and Fang et al. (2008) for consumer-side selection. See Van de Ven and Ellis (2000) and Ellis and Fernandez (2013) for excellent surveys on the concept and issue of risk selection and risk adjustment.

[6]See also Decarolis and Guglielmo (2015), who study changes in insurers' risk-selection behaviors using a Medicare enrollment reform.

[7]See also Geruso and Layton (2015) who interestingly find that insurers manipulate reports to the government about the risk types of enrollees to capitation payments.

petition in insurance markets. Lustig (2011) studies adverse selection and imperfect competition in MA, and Starc (2014) investigates the impact of pricing regulations in Medicare supplement insurance. Recently, Cabral et al. (2014), Duggan et al. (2014), and Curto et al. (2014) study the impact of capitation payments in MA markets. Especially, Curto et al. (2014) use Medicare administrative records, which contain richer information about individual characteristics than we have available and which cover more recent years when capitation payment were adjusted more to variation in expected medical expenditures. They find that healthier individuals still purchase MA and it is still profitable for insurers to attract healthy individuals. However, they also argue that insurers' behaviors do not affect its risk pool. They assume that pricing is an insurer's only tool affecting the risk pool, and they do not find an correlation between an insurer's premium and its risk pool. In this paper, we find that price sensitivity does not vary by individuals with different health status, consistent with theirs. However, we also find that advertising is an important channel of an insurer's risk selection, and as long as risk adjustment is not perfect, pricing decisions substantially depend on the effectiveness of risk selection through advertising. Therefore, our result suggests that evaluating the welfare impacts of risk adjustment designs requires the broader measurement of insurers' risk selection tools.

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, that is, whether advertising gives information about a product or affects utility from the product.[8] More recently, researchers have studied the effects of advertising in an equilibrium framework for different contexts: Goeree (2008) for the personal computer market; Dubois et al. (2014) for junk food markets; and Gordon and Hartmann (2013) and Moshary (2015) for the U.S. elections. 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 health insurance markets affect the marginal cost of providing an additional insurance due to the risk selection, through which pricing and consumer welfare are affected.

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

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

analysis. Section 4 outlines the model, and Section 5 discusses the estimation and identification of the model. Section 6 provides estimates of the model, and Section 7 describes the 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.[9]

The traditional fee-for-service Medicare comprises of Parts A and B, which reimburse costs of medical care utilized by a beneficiary who is covered by Parts A and B. As an alternative to traditional Medicare, a Medicare beneficiary also has the option to receive coverage from an MA plan run by a qualified private insurer. Insurers wishing to enroll Medicare beneficiaries sign contracts with the Centers 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 and so on. 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

[9] 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.

(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 an MA plan.[10] Risk selection was blamed for the selection pattern. MA insurers are not allowed to charge individuals with different health statuses within a county different premiums. More importantly, capitation payments from the government do not fully account for variation in health expenditures across individuals. Until the year 2000, adjustments to capitation payments were made based only on demographic information such as an enrollee's age, gender, welfare status, institutional status, and location, which accounted for only about 1% of an enrollee's expected health costs (Pope et al. 2004). During the period 2000–2003, 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. 2014).

In 2004, the CMS introduced a more comprehensive risk adjustment model called the hierarchical conditional categories (HCC) model in order to reduce incentives for risk selection. The HCC model uses inpatient and outpatient claims to predict the following year's medical expenditures. Based on this prediction, the CMS calculates an individual's risk score with a higher score for a greater expected health expenditure. And an individual's risk score, together with the capitation benchmark for the individual's county of residence, eventually determines the amount of capitation payment an MA insurer receives for enrolling an individual. Brown et al. (2014) find that the new HCC model reduced the returns from enrolling individuals with low risk scores. Even with the HCC model, however, enrolling a low-risk-score individual was still more profitable than a high-risk-score individual. They also find that MA insurers were still able to risk-select individuals who were healthy in dimensions that are not captured by

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

risk scores in the HCC model.

An important feature of this new risk adjustment system is the risk score is calculated based on demographic characteristics for individuals who did not spend at least one full calendar year in the Medicare system, who are likely to be 65- and 66-year old. That is because a past medical history is not available for such individuals. In general, individuals with age 65 or 66 consists of 12% of overall Medicare beneficiaries.

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 2001–2005 for individual-level information on MA enrollment and demographic characteristics, including health status. Our data on mass advertising, through media such as TV, newspaper and radio by health insurers in local advertising markets for the years 2001–2005 were retrieved from the AdSpender Database of Kantar Media, a leading market research firm.[11] Market share data for the years 2001–2005 are taken from the CMS State-County-Plan (SCP) files, and insurers' plan characteristics are taken from the Medicare Compare databases for the years 2001–2005.[12]

Although we use data sets from relatively old periods, we believe our sample periods are still suitable for the purposes of this paper. Importantly, the CMS introduced more sophisticated risk adjustment of capitation payments from 2004 and on, which exogenously changed an MA insurer's profits from enrolling individuals with different health types. The change was likely to create incentives to target different types of consumers, which allows us to investigate how insurers responded to this policy change in terms of the targeting of advertising.

[11] In the Appendix A.2, we also provide supplement analysis using the data for direct mail advertising for the years 2001–2005 from Mintel Comperemedia.

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

3.1.1 Individual-Level Data

The MCBS is a survey of a nationally representative sample of Medicare beneficiaries, which contains information for about 15,000 Medicare beneficiaries every year. The survey is a rotating panel that tracks a Medicare beneficiary for up to four years. This data set provides information on a beneficiary's demographic information such as health status, age, income, education and location. An important feature of this data set is that it is linked to Medicare administrative data, which provide information on an individual's MA insurer choice, the amount of the capitation payment paid for an MA enrollee in the sample, and the amount of Medicare claims costs for individuals in traditional Medicare.

For our analysis, we select our sample using four criteria. First, we only keep individuals who are eligible for Medicare solely because of their ages. Thus, we exclude individuals who are younger than 65 or who are on Medicaid.[13] Second, we exclude individuals who reside in institutions such as nursing homes. We imposed the first and second criteria because we wanted to have relatively homogeneous individuals for predicting an amount of capitation payment for each individual. As mentioned above, the capitation payment for an individual depends on whether he is eligible for Medicaid and whether he resides in an institution. Third, we exclude individuals whose insurance choices last year are not available in the data.[14] We have the third criterion because switching cost is found to be very important in the MA market. Although individuals who just started to receive Medicare benefits do not have a choice made last year, we still include these individuals in the final sample because we do not have any missing information about them.[15] Lastly, we exclude individuals from counties where there was no available MA insurers; these are likely to be rural counties.

[13]To be precise, the first sample criterion also excludes individuals who are eligible for both Medicare and Medicaid.

[14]Because the MCBS is a rotating panel data set, every individual in the data set is not surveyed from the point at which he or she becomes eligible for Medicare. In the first year an individual is surveyed by the MCBS, we would not be able to know the individual's choice last year, so we exclude this observation from our final sample. We are still able to observe which plan an individual in the MCBS from 2001 had in the year 2000 because we do have access to the MCBS from 2000.

[15]These individuals are most likely to be 65 or 66 years old when first surveyed by the MCBS.

3.1.2 Advertising Data

AdSpender contains information on the annual expenditures of mass advertising by health insurers in different media such as TV, newspaper, and radio in the 100 largest local advertising markets in the United States.[16] 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).[17] 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. We use the total advertising expenditure by an insurer in a local advertising market as a measure of the insurer's advertising activity in the market.[18]

3.1.3 Firm- and Market-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, prescription drug coverage, and the copayments associated with primary care doctor visits and specialist visits, skilled nursing facility stays, and inpatient hospital stays.

The CMS State-County-Plan (SCP) files provide the number of Medicare beneficiaries and number of enrollees for each MA insurer. A problem with this data set 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. We deal with this issue by taking the base plan of each MA insurer as a representative plan because the base plan is usually the most popular. As a result, each MA insurer will have only one representative plan available in each county in analysis.

In addition, we also use information on the county-year-level capitation benchmark and the county-year-level per-capita Medicare reimbursement cost for individ-

[16]Given the data periods of our data, the Internet was not a major channel of advertising at least for MA insurers.

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

[18]We did not use advertising expenditures in different media separately since it would be difficult to estimate the effects of advertising in different media on demand separately because of a high positive correlation between expenditures in different media.

Table 1: Summary Statistics at County-Year Level

	No Mass Ad	Small Mass Ad	Large Mass Ad
Total Annual Mass Advertising Expenditure ($1,000)	0	36.4	642
MA Take-up Rates (%)	8.84	16.7	20.3
Capitation Benchmark per Month ($)	550	560	611
Per-Capita per Month Medicare Reimbursement Cost ($)	476	474	547
Number of Medicare Beneficiaries	41,906	51,886	115,785
Average Monthly Premium ($)	45.7	37.7	31.9
Number of Insurers	1.64	2.37	3.48
Number of County-Year Pairs	877	452	457
Number of Insurer-County-Year Combinations	1434	1069	1589

uals in traditional Medicare, which are available from the CMS website. The capitation benchmark determines the overall amount of capitation payment for enrolling an individual in a county and in a year, and the benchmark for a county-year pair is approximately the capitation payment for an individual with the average health status in the county-year.[19]

3.2 Summary Statistics

Table 1 presents summary statistics at the county-year level conditional on total mass advertising expenditures for each market. The first column displays summary statistics for county-year combinations without any mass advertising for MA plans. The second and third columns display summary statistics for county-year combinations with relatively small and large total mass advertising expenditures for MA plans. A county-year's total advertising expenditure is small (large) if it is below (above) the median of total advertising expenditures across county-year combinations.

We find that MA take-up rates are larger in markets with more mass advertising expenditures. The county-year combinations with large advertising tend to be larger in terms of market size (i.e., the number of Medicare beneficiaries in a market). These county-year combinations also have a higher capitation benchmark, but these markets also tend to have higher health care costs measured by higher per-capita reimbursement

[19]The actual amount of the capitation payment for an individual is the product of the individual's risk score and the capitation benchmark for the individual's county in a year. Because the average risk score is normalized to one for the overall Medicare population, the capitation benchmark for a county-year is approximately the capitation payment for an individual with average health status in the county-year.

costs for traditional Medicare. Moreover, county-year combinations with relatively large mass advertising expenditures tend to have more insurers in a market. MA plans in these county-year combinations tend to have lower premiums.

Table 2 presents summary statistics of individuals in the MCBS conditional on insurance status. The first and second columns present summary statistics of individuals that chose traditional Medicare and MA, respectively. We find that a majority of individuals do not switch between the traditional Medicare and MA. For those who choose the traditional Medicare, more than 90% chose traditional Medicare last year, although only 70% of overall Medicare beneficiaries chose traditional Medicare last year. Likewise, about 85% of those who choose MA this year also chose MA last year, although only 20% of the overall Medicare beneficiaries had MA last year. Also, we find that health and income status of MA enrollees are different from those at traditional Medicare. We construct a binary health status, healthy or unhealthy, based on self-reported health status.[20] Our income measure is constructed as a five-level categorical variable, with five being the category for the highest income, based on the income variable in the MCBS.[21] We find that healthy individuals are more likely to choose MA, which is consistent with the findings of previous research on MA, as mentioned earlier. Moreover, we find that those who choose MA are more likely to have lower income and be female, although the average ages between the two groups of individuals are not very different.

Table 3 presents summary statistics on relationships between an individual's specific health measures and the individual's choice of MA plan. We consider switching patterns of individuals, which are now classified into (1) individuals who do not switch or individuals who switch but choose traditional Medicare; (2) individuals who switch to MA plans which do not advertise; (3) individuals who switch to MA plans which do advertise. Each row in the table provides specific measures of health status. We calcu-

[20] An individual's health status is defined to be healthy if the self-reported health status is "Excellent," "Very Good," or "Good." An individual's health status is defined to be unhealthy if the self-reported health status is "Fair" or "Poor."

[21] Although MCBS income variable has eleven categories originally, we create a new variable with five categories in order for the income measure in the MCBS to be compatible with the income measure in the Mintel data. Eventually, the new income variable we create is equal to one, two, three, four, or five if an individual's income belongs to the following five intervals, respectively: $[0, 15000)$, $[15000, 25000)$, $[25000, 35000)$, $[35000, 50000)$, and $[50000, \infty)$. Henceforth, when we refer to an individual's income in the MCBS, we refer to the new income variable with the five categories.

Table 2: Summary Statistics at Individual Level

	Traditional Medicare (TM)	MA	Overall
Chose TM Last Year (%)	90.1	4.24	70.9
Chose MA Last Year (%)	1.51	85.7	20.3
New Medicare Beneficiary (%)	7.04	5.66	6.73
Healthy (%)	83.0	84.7	83.4
Age	75.5	75.2	75.5
Income = 1 (%) (lowest)	2.0	1.9	2.0
Income = 2 (%)	30.2	37.8	31.9
Income = 3 (%)	32.1	35.2	32.8
Income = 4 (%)	18.7	15.6	18.0
Income = 5 (%) (highest)	17.0	9.5	15.3
Observations	16725	4986	21711

late the statistics separately for markets with advertising spending below the median (Small Mass Ad in the table) and those with spending above the median (Large Mass Ad in the table). A striking finding is that individuals who switch to MA plans with advertising has in better conditions in terms of cognition, vision and activities of daily living than those who switch to MA plans without advertising. The result suggests that advertising can potentially have heterogeneous effects on individuals depending their health status. Individuals with vision problems will be less exposed to advertising, and advertising will be less effective on those with having problems with cognition and activities of daily livings. Because there are other plans characteristics that may have differential effects depending on health status, we estimate later the effect of advertising depending on health status with the demand model that controls for other plan characteristics.

3.3 Preliminary Analysis

Now, we provide evidence that insurers geographically target mass advertising to markets where risk selection will be more profitable.[22] As mentioned earlier, many previ-

[22]We are actively revising the paper currently. In the process, we are adding data from 2006 and 2007 in addition to the existing data. The current preliminary analysis showing geographical targeting of mass advertising is done with data from 2001–2007. We are in the process of acquiring the MCBS from 2006 and 2007 but do not have them at hand. Thus, our structural estimation of the model is done with data from 2001–2005, but we plan to re-estimate the model with the newer data.

Table 3: Summary Statistics at Individual Level: Relationship between Individual Health and Advertising

	Small Mass Ad			Large Mass Ad		
	No switching or not choosing MA	Switch to MA with no adv	Switch to MA with adv	No switching or not choosing MA	Switch to MA with no adv	Switch to MA with adv
Cognition problem	0.141	0.147	0.115	0.129	0.188	0.089
Vision problem	0.290	0.313	0.281	0.284	0.282	0.224
Daily living activities problem	0.208	0.169	0.135	0.199	0.155	0.131
Age	75.833	72.802	72.198	75.897	72.617	72.263

Note: Cognition problem is a dummy variable that equals to one if an individual in the MCBS data has a problem with making decisions such that it interferes daily activities, has a trouble in concentrating or experience memory loss such that it interferes daily activities. Daily living activities problem is a dummy variable that equals to one if an individual in the MCBS has a problem with shoppping, managing money, using telephone or doing light household works.

ous works find that an imperfect risk adjustment provides incentives for risk selection. Even after a more comprehensive risk adjustment regime was introduced in 2004, researchers tend to find favorable risk selection. Brown et al. (2014) find that the new risk adjustment regime still did not account for Medicare costs for unhealthy individuals. According to their calculation, the capitation payments are estimated to be larger than their expected Medicare costs for 77% of individuals before and after the new risk adjustment regime. Newhouse et al. (2014) argue that the extent of risk selection is reduced after 2004 but that the favorable risk selection still remains. In the Appendix A.1, we also show using our data that MA insurers indeed have incentives for risk selection before and after the new risk adjustment regime.

More importantly, as we discuss in the Section 2, a more comprehensive risk adjustment system depending on the past medical history was introduced in 2004 *only* for individuals who stay the Medicare system at least one full calender year. For new Medicare enrollees, their risk scores remained based on demographic information. Therefore, after 2004, the gain from risk selection may depend more on size of new Medicare beneficiaries, which may affect advertising behaviors for insurers. To test this hypothesis, we run the following regression: for each county (market) m at year t, the county level advertising expenditure ad_{mt} follows

$$ad_{mt} = POP_{mt}^{64-65}\mathbf{1}\left[t \geq 2004\right]\beta_1 + POP_{mt}\mathbf{1}\left[t \geq 2004\right]\beta_2 + X_{mt}\gamma + f_t + f_m + \varepsilon_{jct}$$

Table 4: Geographical Targeting of Mass Advertising

	ad_{mt}	ad_{mt}
$POP_{mt}^{64-65}\mathbf{1}[t \geq 2004]$	0.133 (0.0220)***	0.137 (0.0246) ***
Observations	9,065	9,065
R-squared	0.657	0.672

Note: In order to save space, we do not report estimate for all coefficients here. Table 18 in the Appendix provide the complete results.

where X_{mt} is the vector of market level characteristics, including the number of insurers, county-level capitation benchmark, Fee For Service (FFS) Medicare costs (healthcare cost), and their interactions (including POP_{mt}^{64-65},POP_{mt},$\mathbf{1}[t \geq 2004]$). We also incorporate both year and market fixed effects. Our interested parameter is β_1, the coefficient of the population size of age between 64 and 65 interacted with the dummy whether the year t is after the risk adjustment reform. With the market fixed effect, a likely source of data variation to identify this parameter is changes in advertising spending before and after 2004 across markets with different sizes of age 64-65 population.

Table 4 shows the regression result. We find that the the coefficient of the population size of age between 64 and 65 interacted with the dummy whether the year t is after the risk adjustment reform is positive and significant, which is consistent with our hypothesis that advertising is more responsive to the profitability of risk selection. Therefore, if insurers can attract healthy individuals with advertising, they will have greater incentives to advertise more in a market where attracting a healthy individual results in greater profit. It is important to emphasize that we have yet to show direct evidence on how advertising can achieve risk selection. In order to show how advertising achieve risk selection, we must take into other factors affecting individual health insurance purchase decisions which may be correlated with advertising. In the following sections, we will provide the evidence from our structural demand model that advertising tends to attract healthy types more than unhealthy types.

4 Demand Model

We now investigate how advertising affects consumer demand by structurally estimating a model of health insurance demand. Although we provided evidence for the targeting of both direct mail and mass advertising, we only consider the impact of mass advertising on demand. One difficulty of using the data on direct mail in the demand analysis is that it is difficult to link the direct mail data (Mintel) to the data on a consumer's insurer choice (MCBS). The number of individuals in a county-year in the Mintel data is not large enough to construct a measure of direct mails sent to a county-year. Thus, without combined information on advertising exposure and subsequent choice, it will be difficult to estimate the effects of direct mail on demand for MA.[23] Moreover, as shown in the previous section, we do not find evidence that the change in the targeting of direct mail led to a corresponding change in demand for MA.

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 and different years face different choice sets. Thus, we will naturally define a market of MA as a combination of county-year (ct). 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. The advertising market m, to which county c belongs, is denoted by $m(c)$.

Each MA market (ct) has J_{ct} MA insurers available. An individual in a market also has the option of choosing traditional Medicare. Thus, an individual has the total $J_{ct}+1$ options in MA market ct. An insurer j in market ct can be described by a combination of advertising $(ad_{jm(c)t})$, other observed characteristics (x_{jct}) including premium and plan characteristics, county fixed effect (μ_c), an insurer-year fixed effect $(\overline{\xi_{jt}})$, and an unobservable characteristic $(\Delta\xi_{jct})$. A consumer i can be described by a combination of health status (h_i), last year's choice of insurer $(d_{i,t-1})$, other observed characteristics (c_{it}), and a preference shock (ε_{ijct}). We will explain each insurer's and individual's characteristics after we describe an individual's utility from an insurer.

Consider an individual i living in county c and year t. Consumer i chooses to enroll with one of the available J 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

[23] One possibility is to impute the number of MA mailings an individual receives using characteristics present in both data sets. Unless we can do the imputation precisely, the impact of imputed mailings on demand is likely to be estimated with a substantial bias.

MA insurer j as follows:

$$u_{ijct} = \ln\left(1 + ad_{jm(c)t}\right)\alpha_{ijt} + x_{jct}\beta_{it} + \phi_{ict}\mathbf{1}[d_{i,t-1} \neq j, d_{i,t-1} \geq 0] + \mu_c + \overline{\xi_{jt}} + \Delta\xi_{jct} + \varepsilon_{ijct} \quad (1)$$

where

$$\begin{aligned} \alpha_{ijt} &= \alpha_0 + \alpha_1 \mathbf{1}[d_{i,t-1} = j]h_{it} + \sum_{k=0}^{1} \alpha_{2,k}\mathbf{1}[d_{i,t-1} \neq j]\mathbf{1}[h_{it} = k]; \\ \beta_{it} &= \beta_0 + \beta_1 h_{it}; \\ \phi_{ict} &= \phi_0 + \phi_1 h_{it} + \phi_2 J_{ct} + \phi_3 J_{ct}^2. \end{aligned}$$

A consumer's outside option is to enroll in traditional Medicare, from which a consumer receives utility of u_{i0ct}:

$$u_{i0ct} = h_{it}\rho_1 + c_{it}\rho_2 + \phi_{ict}\mathbf{1}[d_{i,t-1} \neq 0, d_{i,t-1} \geq 0] + \varepsilon_{i0ct}. \quad (2)$$

Both an individual's characteristics and an insurer's characteristics determine u_{ijct}. An individual's characteristics included in u_{ijct} are individual i's binary health status h_{it} that equals to one if healthy (and zero if unhealthy), last year's insurance choice $d_{i,t-1}$, and other relevant individual characteristics c_{it}. Last year's insurance choice $d_{i,t-1}$ contains information about (i) whether individual i chose MA or traditional Medicare last year and (ii) which MA insurer this individual chose if MA was chosen last year. In case that individual i is new to Medicare, we set $d_{i,t-1} = -1$, and thus $\mathbf{1}[d_{i,t-1} \neq j, d_{i,t-1} \geq 0] = 0$ for any j for new Medicare beneficiaries.[24] Lastly, ε_{ijct} is an individual i's preference shock for insurer j, which we assume is distributed as the Type I extreme value distribution.

Each insurer has observable characteristics ($ad_{jm(c)t}$ and x_{jct}), county fixed effect (μ_c) and an insurer-year fixed effect ($\overline{\xi_{jt}}$), and an unobservable characteristic ($\Delta\xi_{jct}$). First, ad_{jmt} denotes insurer j's advertising expenditure in millions in advertising mar-

[24]We define an individual as new to Medicare if he or she has spent less than two years on Medicare as of the end of year t.

ket m in year t.[25] [26] Note that the effects of advertising diminish in its expenditure because $ad_{jm(c)t}$ enters u_{ijct} in logarithm.[27] The effect of advertising on indirect utility u_{ijct} is captured by α_{ijt}, which depends on individual i's previous insurance status $d_{i,t-1}$ and self-reported health status h_{it}. In other words, insurer j's advertising has different effects, depending on whether individuals chose the insurer last year and whether an individual is healthy. Parameter α_0 represents the effects of advertising that are independent of an individual's characteristics. Parameter α_1 represents the effects of advertising for healthy consumers who chose the same insurer last year. And $\alpha_{2,0}$ and $\alpha_{2,1}$ capture the effects of advertising on unhealthy and healthy individuals that did not choose insurer j last year, respectively.

We distinguish the effects of advertising on individuals who chose the advertised insurer last year and those who did not because if advertising is informative, it will be more effective for individuals who did not choose the insurer (Ackerberg, 2001). Informative advertising is likely to provide information about an insurer's unobserved quality or simply the existence of the insurer in the market. Thus, it is plausible that this type of advertising will have little effects on individuals who chose the insurer last year. On the other hand, if advertising has prestige or image effects, then it will likely affect both types of individuals. Moreover, advertising can be still informative for an individual who already enrolled with the advertised insurer. Unless an individual receives much medical care, the individual will not be able to know an insurer's true unobserved quality. Advertising can still provide information to such an individual.

Moreover, we allow for the possibility that advertising has a different impact depending on h_{it}. If the impact of advertising depends on h_{it}, then advertising will eventually affect an insurer's risk pool and thereby its cost. In this case, advertising can be used for risk selection. In principle, there are two interpretations of the heterogeneous impacts of advertising depending on h_{it}: the targeting of mass advertising

[25]Note that advertising affects demand through the indirect utility function in our model. Alternatively, one can model specific channels through which advertising affects demand: for example, a consumer's awareness of a product, providing experience characteristics of product quality, or enhancing prestige or image of a product. We do not take this approach, however, because separately identifying different effects of advertising is challenging with our data.

[26]This specification assumes no interaction term between advertising and price. We also estimated the version of the model allowing those interactions and also further allow interaction with them to individual last year's insurance status. However, none of them are statistically significant and therefore we decided to drop for this estimation. Estimates for the specification are available on request.

[27]Because $ad_{jm(c)t}$ is zero for many insurers, we use $\ln\left(1+ad_{jm(c)t}\right)$ instead of $\ln\left(ad_{jm(c)t}\right)$.

at certain types of consumers and a consumer's differential response to advertising. First, targeting refers to the possibility that an insurer targets its advertising at certain TV programs and newspapers that are more exposed to a certain health type than to another type. Note that this kind of targeting requires an insurer to employ a more sophisticated targeting strategy than targeting certain counties. Second, a consumer's differential response to advertising refers to the possibility that a certain health type responds to advertising more than another health type. In this case, advertising can still affect a certain type's demand disproportionately more even without sophisticated targeting. Unfortunately, we cannot clearly distinguish the two different channels because we do not have information about which types of consumers were exposed to an MA insurer's mass advertising.

However, we view that the heterogeneous impacts are likely to capture the second mechanism for the following reasons.[28] First, even without sophisticated targeting, health status itself can determine how much an individual is exposed to advertising. For example, mass advertising mostly appears on TV or in newspapers, and those who are able to watch TV or read newspapers are less likely to have their vision or hearing problems. We find that unhealthy individuals are more likely to have vision or hearing problems in the MCBS, as shown in Table 19 in the Appendix.[29] Moreover, among those who have such problems, unhealthy individuals are more likely to believe that their vision or hearing problems make it difficult for them to obtain information about Medicare, as reported in Table 19 in the Appendix.[30] Thus, those who actually respond to advertising will be more likely to be healthy even without sophisticated targeting. This pattern is indeed consistent with the summary statistics in Table 3. Second, as Fang et al. (2008) argue, a health status is highly correlated with cognition abilities

[28]In case that the heterogeneous impacts capture an insurer's targeting to some extent, then a potential problem is that parameter α_{ijt} is not policy-invariant for our counterfactual analysis. That is because an insurer may target its advertising at a different health type with a counterfactual change in its incentives to attract different health types. In our counterfactual analysis, however, we exogenously shut down advertising in order to investigate the impact of advertising on the MA market. In this case, parameter $\alpha_{1,k}$ will not play any role in this counterfactual analysis. Thus, results in our counterfactual analysis will not depend on whether the heterogeneous impacts capture the targeting.

[29]The Table 19 in the Appendix presents results for regressions of whether an individual has a vision or hearing problem on his health status and age.

[30]The Table 19 in the Appendix also presents results for regressions of whether an individual believe that his vision or hearing problems make it difficult to obtain information about Medicare on his health status and age.

for elderly people, which may lead to a differential response to advertising. Third, we investigate whether insurers conduct within-market advertising targeting using the data from direct mail advertising. The analysis is shown in the Appendix A.2. We find evidence that direct mail advertising is sent to certain individuals, with whom insurers can potentially make more profits through the risk selection. However, we do not find the evidence that those individuals subsequently purchase MA, indicating that the targeting of advertising at certain individuals within a market was not very effective in attracting them to MA. Because targeting mass advertising at certain individuals is plausibly more difficult than targeting via direct mail, we believe that it will be difficult for insurers to risk-select through targeting mass advertising at healthy types.

The term x_{jct} denotes a vector of insurer j's observed characteristics other than advertising, which include the premium, copayments for a variety of medical services such as inpatient care and outpatient doctor visits, and variables describing whether an insurer offers drug coverage, vision coverage, dental coverage, and so on. We define the premium to be the amount that a consumer pays in addition to the Medicare Part B premium.[31] The effects of plan characteristics on utility are potentially heterogeneous depending on an individual's health type. For example, an MA insurer offering drug coverage may be preferred by individuals who expect a large expenditure on prescription drugs, and a private fee-for-service MA insurer may be preferred by a certain health type because its provider network is not as restrictive as an HMO. We also allow for the possibility that disutility from a premium depends on a healthy type because different health types may have different willingness to pay for MA. The heterogeneous effects are captured by parameter β_{it}, which depends on an individual's health h_{it}.[32]

The term ϕ_{ict} denotes switching cost of changing insurers. Note that $\mathbf{1}[d_{i,t-1} \neq j, d_{i,t-1} \geq 0]$ is equal to one if an individual, who is not new to Medicare, chooses a different plan from one chosen last year. This means that new Medicare beneficiaries

[31] When enrolling in an MA plan, an individual must pay the Medicare Part B premium as well as the premium charged by the plan. Here we do 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.

[32] 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 Table 5.

do not pay a switching cost for their initial choice of insurer. Notice that the switching cost makes the impact of advertising on demand depend on $d_{i,t-1}$. Because new Medicare beneficiaries do not face a switching cost, advertising will have a larger effect on them. We also allow for the possibility that ϕ_{it} is different, depending on h_{it} and J_{ct} (number of available insurers in a market). We let J_{ct} affect ϕ_{ict} because the functional-form assumption for ε_{ijct} mechanically implies that an individual in a market with more insurers is more likely to switch to a different plan with all others being equal.

The term $\overline{\xi_{jt}}$ denotes insurer-year fixed effects that capture an insurer j's brand effect in year t. Moreover, μ_c represents county fixed effects, which capture county-specific factors that determine demand for MA in the county. An individual's utility also depends on aspects of an insurer that are unobserved by researchers but observed by consumers and insurers. The term $\Delta\xi_{jct}$ is a deviation from μ_c and $\overline{\xi_{jt}}$, and $\Delta\xi_{jct}$ captures 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, we discuss the specification of utility for the outside option, which is traditional Medicare. Note that the constant term for u_{i0ct} is normalized to zero because the term cannot be identified in a discrete choice model. All of the terms included in u_{i0ct} are individual characteristics such as health status, switching cost, and other characteristics denoted by c_{it}, which include age, income, and interaction between year and previous insurance status. These individual characteristics capture different utilities from the outside option for individuals with different characteristics, relative to their utility from MA insurers in general.

5 Identification and Estimation

For the discussion of identification and estimation of the model, we define θ to be a vector that contains all parameters in the model. For our discussion in this section, let $\theta \equiv (\theta_0, \theta_1)$, where θ_0 is a collection of parameters that determine the parts of utility independent of individual heterogeneity and where θ_1 is a collection of parameters that determine preference heterogeneity resulting from individual characteristics. That is, $\theta_0 \equiv (\alpha_0, \beta_0)$, and θ_1 contains all other parameters in equations (1) and (2).

Mean Utility First, we discuss the identification of parameters in θ_0. The parts of u_{ijct} in equation (1) that are independent of individual heterogeneity are usually called mean utility δ_{jct}. In other words,

$$\delta_{jct} \equiv \ln\left(1+ad_{jm(c)t}\right)\alpha_0 + x_{jct}\beta_0 + \overline{\xi_{jt}} + \mu_c + \Delta\xi_{jct}. \tag{3}$$

Berry et al. (1995) show that given a value for θ_1, there is a unique $\delta^*_{jct}(\theta_1)$ that exactly match predicted market shares to observed market shares. Then parameter θ_0 is estimated using equation (3) by treating $\Delta\xi_{jct}$ as a structural error term. A well-known problem regarding the identification of θ_0 is that $\Delta\xi_{jct}$, which may capture unobserved product characteristics, and endogenous plan characteristics included in the model are correlated. This problem is a typical endogeneity problem, and then a simple ordinary-least-squared regression of $\delta^*_{jct}(\theta_1)$ on (ad_{jmt}, x_{jct}) will result in inconsistent estimates of θ_0 if $(ad_{jm(c)t}, x_{jct})$ contains endogenously chosen characteristics. We assume that the advertising expenditure $ad_{jm(c)t}$ and the premium p_{jct}, which is a part of x_{jct}, are endogenous variables. Although almost all of the plan characteristics are potentially endogenous, we assume that these characteristics are exogenous in this estimation. A crucial reason for this decision is that the number of instruments required for consistent estimation should be at least as great as the number of endogenous variables included in $(ad_{jm(c)t}, x_{jct})$. Given the large number of plan characteristics, it is extremely difficult to come up with instruments for all of them.

Although the endogeneity problem challenges the identification, the fixed effects μ_c and $\overline{\xi_{jt}}$ included in δ_{jct} is likely to control for a significant part of the unobserved heterogeneity of insurers. However, it is still possible that $\Delta\xi_{jct}$ still contains unobserved characteristics that are varying over insurers, counties and years. 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 use instruments similar to ones used by Hausman (1996) and Nevo (2001).[33] In other words, we use the average advertising expenditures of the same parent companies in other advertising markets for $ad_{jm(c)t}$ and the use the average premium of the same parent company in other counties for p_{jct}. The instruments capture the idea that an insurer's marginal cost contains a component that is common to all subsidiaries of a parent

[33] Town and Liu (2003) also use a similar instrument in estimating a model of demand for MA plans.

company, which is assumed to be uncorrelated with the unobserved heterogeneity. Resulting moment conditions employed in the estimation are that $E[\Delta\xi_{jct}|\Gamma] = 0$, where Γ is a set of instruments that includes the aforementioned two sets of instruments as well as x_{jct}.

Preference Heterogeneity Important information for the identification of parameters for preference heterogeneity θ_1 is an individual's insurer choice from the MCBS (the individual-level data). Parameter θ_1 will be identified by variation in the characteristics of insurers chosen by individuals having different characteristics. An important parameter in θ_1 are the parameters that determine the heterogeneous effect of advertising depending on an individual's health type and last year's choice, which are $\alpha_1, \alpha_{2,0}$ and $\alpha_{2,1}$ in (1). These parameters will be identified by variation in individuals' switching patterns across health types, last year's choices, and advertising expenditures by insurers they are switching to.

In order to construct micro-moments for an individual's choice and combine them with the aggregate moments, we use the score of the log-likelihood function for a choice by an individual observed in the MCBS, as in Imbens and Lancaster (1994). The likelihood function for an individual's choice is $L = \prod_{i,j,c,t} q_{jct}(z_i)^{d_{ijct}}$, where $q_{jct}(z_i)$ is the probability that an individual with characteristics z_i chooses an insurer jct, and d_{ijct} is an indicator variable that equals one when individual i chooses plan jct. Then our micro-moments are $\partial \log(L)/\partial\theta_1 = 0$.

6 Demand Side Estimates

Table 5 displays estimates for important parameters in the demand model. The effects of advertising on an individual's demand is the sum of the common effects (the coefficient in front of $\log(1 + ad_{jmt})$) and the heterogeneous effects (the coefficients for interaction terms). Based on the estimates, we find that the effect of advertising on demand is much greater for healthy individuals ($h_{it} = 1$), especially for healthy individuals who are switching or new to Medicare ($\mathbf{1}[d_{i,t-1} \neq j, d_{i,t-1} \geq 0] = 1$). In addition, the estimate for disutility from a premium is negative and statistically significant, but the estimate for the interaction between a premium and the dummy variable for the healthy type is not statistically significant. This means that healthy and unhealthy

Table 5: Estimates for Parameters of Interest

Variables	Estimates	Std. Error	Variables	Estimates	Std. Error
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}\neq j]\times\mathbf{1}[h_{it}=1]$	1.449***	(0.612)	$\mathbf{1}[d_{i,t-1}\neq j, d_{i,t-1}\geq 0]$	-3.786***	(0.242)
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}=j]\times h_{it}$	0.879*	(0.485)	$\mathbf{1}[d_{i,t-1}\neq j, d_{i,t-1}\geq 0]\times h_{it}$	0.016	(0.127)
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}\neq j]\times\mathbf{1}[h_{it}=0]$	0.470	(0.467)	$\mathbf{1}[d_{i,t-1}\neq j, d_{i,t-1}\geq 0]\times J_{ct}$	0.008	(0.084)
$\log\left(1+ad_{jmt}\right)$	-0.546**	(0.268)	$\mathbf{1}[d_{i,t-1}\neq j, d_{i,t-1}\geq 0]\times J_{ct}^2$	-0.007	(0.008)
Premium	-0.015**	(0.006)	Drug Coverage	0.358***	(0.088)
Premium$\times h_{it}$	3.2e-4	(0.003)	Drug Coverage$\times h_{it}$	0.0147	(0.215)

consumers do not have very different price sensitivity.

In order to put the estimates for parameters for advertising and premiums into perspective, we calculate the semi-elasticities of demand with respect to advertising and premiums, which are presented in Table 6.[34] Semi-elasticity of demand with respect to a premium is -0.847%, which means that a dollar increase in an insurer's premium will lead to a decrease in demand for the insurer by 0.847%. Although the semi-elasticities for the two different health types are slightly different, it is unlikely that the difference is statistically significant given the imprecise estimate for the coefficient that determines a healthy consumer's price sensitivity relative to a unhealthy consumer. This finding is consistent with Curto et al. (2014).

For the effect of advertising on demand, we calculate the semi-elasticity of demand with respect to advertising for an increase of $2,300 of advertising expenditures, which is about 1% of the average advertising expenditure among insurers with positive advertising expenditures. We find that an additional $2,300 in an insurer's advertising expenditure increases demand for the insurer by 0.066% on average. Semi-elasticities for different health types show that the effects of advertising are substantially different across different health types. A healthy consumer's average semi-elasticity is 0.086% whereas an unhealthy consumer's semi-elasticity is close to zero.

Variables other than advertising and premiums are also important in determining demand for an MA insurer. We find that the switching cost is very important in explaining an individual's demand, although the cost is not very different across individuals with different health types and in different markets. The important role of the switch-

[34]Semi-elasticity of demand Q with respect to a variable x is defined as $\frac{\partial Q}{\partial x}\times\frac{1}{Q}$, which measures a percentage change in Q with a unit increase in x. We calculate semi-elasticities instead of elasticities because an advertising expenditure and a premium are zero for 68% and 37% of insurers, respectively. When an advertising expenditure is zero, elasticity of demand with respect to advertising becomes zero. The same result is also true for elasticity of demand with respect to premiums.

Table 6: Elasticity of Demand with Respect to Advertising and Premiums

Semi-Elasticities of Demand	Adv ($2,300)	Premium ($1)
Overall Semi-elasticity	0.066%	-0.847%
Semi-elasticity for *healthy*	0.086%	-0.851%
Semi-elasticity for *unhealthy*	-0.012%	-0.943%

Note: $2,300 = 1% of mean advertising spending for insurers with positive amounts.

ing cost in our results is consistent with findings by other papers on health insurance markets.[35] In addition, the provision of drug coverage has a positive and significant effect on demand, which reflects the fact that during our data period (2001–2005), the drug coverage would not be available if an individual chose traditional Medicare. However, the interaction of drug coverage and the healthy dummy is not significant. Lastly, estimates for all other parameters are reported in Table 20 and 21 in the Appendix.

7 Counterfactual Experiments

With the estimated model, we conduct counterfactual analyses to understand the impact of risk selection through advertising on the MA market. In order to quantify the impact of advertising on the MA market, we simulate the model by exogenously setting every insurer's advertising expenditure to zero. We simulate the model under two different counterfactual scenarios. In the first scenario, we assume that a premium is fixed exogenously at its level in the baseline. In the second scenario, we assume that insurers can reoptimize their premiums in the counterfactual environment. In this case, we investigate the equilibrium impact of shutting down advertising on market outcomes. We believe that modeling equilibrium price responses is important to better understanding advertising as playing a role in risk selection and its implications for consumer demand and ultimately welfare.

In order to obtain its impact on equilibrium, we first need to specify a model of how MA insurers choose their premiums. Therefore, we discuss the model of the supply side before simulating our model.

[35] For example, see Handel (2013), Ho et al. (2015), Miller (2014), Miller et al. (2014), Nosal (2012), and Polyakova (2014).

7.1 Model of the Supply Side

We assume that insurers play a simultaneous game in choosing optimal pricing in each market (county-year).[36] When insuring an individual i with characteristic z_i, insurer jct expects to incur a marginal cost $c_{jct}(z_i)$ as follows:

$$c_{jct}(z_i) = E_\omega[m(z_i, x_{jct}, \omega_{ijct}; \lambda)] + \eta_{jct}, \tag{4}$$

where $m(z_i, x_{jct}, \omega_{ijct}; \lambda)$ is a realized reimbursement cost for an individual with characteristic z_i who choose plan jct. The term ω_{ijct} represents a random chock to the reimbursement cost, and λ represents parameters to be estimated. Next, η_{jct} is a insurer-county-year-specific shock to marginal cost that is constant across individuals having different z_i. We assume that η_{jct} is observed by all insurers when making a pricing decision. Note that the expected marginal cost $c_{jct}(z_i)$ depends on the consumer's characteristic z_i, which includes health status. Therefore, an insurer's costs will eventually depend on what kinds of individuals are enrolled with the insurer.

We estimate the marginal cost parameters λ using the individual-level information from the MCBS on how much an individual's MA insurer paid for the individual's medical care in a year. Details on the exact functional form of $m(z_i, x_{jct}, \omega_{ijct}; \lambda)$ and estimation of λ are reported in Appendix A.3.

Insurer j's profit from a county c in year t is given by

$$\pi_{jct} = M_{ct} \int\limits_{z_i} (p_{jct} + cp(z_i) - c_{jct}(z_i)) q_{jct}(z_i) dF_{ct}(z_i) - C(ad_{jm(c)t}), \tag{5}$$

where M_{ct} is the population of those who are at least 65 years old in county c in year t, and p_{jct} is the premium charged by insurer j in county c in year t.[37] Next, $cp(z_i)$ is the

[36] Because we do not consider counterfactual situations where MA insurers re-optimize their advertising expenditures, we do not consider the optimal advertising decision here.

[37] One important assumption we made is that firms are myopic. With an individual's switching cost, an MA insurer potentially has a dynamic pricing incentive. Miller (2014) is the first attempt to estimate a model with forward-looking insurers in the MA market. One alternative is to follow the approach by Decarolis et al. (2015), who also estimate an equilibrium insurance market model with switching costs and myopic firms. In order to correct for possible bias resulting from ignoring dynamic pricing incentives, they do a robustness check on whether the estimates of marginal cost are biased at a certain level. Fully characterizing the dynamic pricing decision is a very challenging task and left to future work.

expected capitation payment for an individual having characteristics z_i. We calculate $cp(z_i)$ based on the relationship between the observed amount of capitation payment and z_i in the MCBS. The details about the calculation can be found in Appendix A.1. Lastly, $q_{jct}(z_i)$ is the probability of choosing insurer j by an individual having characteristics z_i. Lastly, $C(ad_{jm(c)t})$ denotes the advertising cost for each firm, which captures both the variable and fixed costs associated with ad_{jct}.

With the profit equation, it is clear how risk adjustment and advertising affect profits. With a perfect risk adjustment of capitation payment, $cp(z_i) - c_{jct}(z_i)$ is constant across z_i. In this case, a healthy individual will not cost less than an unhealthy individual, and advertising will affect an insurer's profit just by increasing the overall demand for the insurer $\int_z q_{jct}(z_i)dF_{ct}(z)$. With an imperfect risk adjustment, in contrast, $cp(z_i) - c_{jct}(z_i)$ will depend on z_i and will be typically larger for healthy individuals, which is the case for the MA market. In this case, advertising affects an insurer's profit through an insurer's cost $\int_z c_{jct}(z_i)q_{jct}(z_i)$ as well as through the overall demand.

The Nash equilibrium condition for the optimal pricing game for insurers is that insurers' choices maximize their profits given choices made by other insurers. Thus, we have the following condition for each p_{jct} such that $\partial\pi_{jct}/\partial p_{jct} = 0$. We can solve for η_{jct} in a way that is similar to Berry et al. (1995). Appendix A.3 provides details on how we solve for η_{jct}.

7.2 Simulation Results

We now evaluate the effects of shutting down advertising on the MA market under two different scenarios. First, we assume that a premium is fixed at its baseline level exogenously. Second, we assume that insurers can reoptimize their premiums. Henceforth, we will refer to the first and second counterfactual scenarios as the "Partial Eq" and the "Full Eq" counterfactual.

Table 7 summarizes the effects of shutting down advertising on a consumer's switching patterns, depending on a consumer's insurance choice last year. For each group of consumers, we calculate the effects on demand separately for markets with different levels of advertising expenditures. First, we compare results in the baseline and those in the counterfactual where premiums are fixed, which are presented under the columns labeled "Partial Eq." As expected, the probability of switching to MA will be lower in

Table 7: Counterfactual: Individual Demand

	Markets with Small Adv			Markets with Large Adv			Markets with Any Ad		
Health Type	Baseline	Partial Eq	Full Eq	Baseline	Partial Eq	Full Eq	Baseline	Partial Eq	Full Eq
	Panel 1: Consumers That Are New to Medicare: Pr(Switching to MA)								
Healthy	0.177	0.175	0.171	0.228	0.205	0.199	0.208	0.193	0.188
Unhealthy	0.196	0.196	0.190	0.212	0.212	0.206	0.207	0.207	0.201
	Panel 2: Consumers That Chose Traditional Medicare Last Year: Pr(Switching to MA)								
Healthy	0.0170	0.0167	0.0162	0.0174	0.0151	0.0141	0.0172	0.0158	0.0150
Unhealthy	0.0148	0.0148	0.0144	0.0133	0.0133	0.0125	0.0139	0.0139	0.0133
	Panel 3: Consumers That Chose a MA Plan Last Year: Pr(Switching to different MA)								
Healthy	0.0368	0.0365	0.0365	0.0716	0.0679	0.0706	0.0605	0.0578	0.0597
Unhealthy	0.0351	0.0349	0.0348	0.0709	0.0667	0.0702	0.0596	0.0567	0.0591

Note: Markets with Small Adv refers to a set of markets where market-level total advertising expenditures are below the median of market-level total advertising expenditures; Markets with Large Adv refers to a set of markets where market-level total advertising expenditures are above the median of market-level total advertising expenditures.

the counterfactual situation than in the baseline, regardless of a consumer's insurance status last year. Moreover, the probability of switching to MA is much greater for a new Medicare beneficiary because a new Medicare beneficiary does not face switching costs. Therefore, the effect of advertising on demand is much greater for a new Medicare beneficiary in terms of an absolute change in probabilities of switching to MA. This indicates that it is important to look at *flows* instead of *stocks* in order to understand the effect of advertising on demand. We also find that the decrease in the probabilities will be greater in markets with larger advertising expenditures. This result shows that an insurer's geographical targeting of advertising plays an important role in explaining cross-market differences in demand for MA.

Next, we investigate the impact of advertising on demand in the "Full Eq" counterfactual. Compared with the results in the other counterfactual situation where premiums are fixed, we find more substantial declines in overall probabilities of switching to MA for individuals that new to Medicare and those who chose traditional MA last year. In contrast, the probability of switching for those who chose a MA insurer last year in the "Full Eq" counterfactual is greater, compared with the "Partial Eq" counterfactual.

In order to understand the difference between the results in the two counterfactual situations, we analyze how new equilibrium premiums in the "Full Eq" counterfactual are different from the premiums in the baseline. Table 8 reports equilibrium premiums and market shares in different counterfactual situations. We report the results for two groups of insurers, depending on whether they advertise at all in the baseline economy. First, insurers with positive baseline advertising expenditures will increase premium in the "Full Eq" counterfactual. We find that the increase in the average premium will be much larger in the markets with relatively large baseline advertising expenditures than for the markets with relatively small baseline expenditures. In the former group of markets, insurers with positive baseline advertising expenditure will increase monthly premiums by about 40% from $20.6 to $28.8 (or from $247.2 to $345.6 annually). Such a large increase in premiums will keep individuals who did not choose MA last year from switching to MA in the "Full Eq" counterfactual. Second, insurers with zero baseline advertising expenditures will decease their monthly premiums by about 19% from $18.6 to $15.0 (or from $223.2 to $180.0 annually). Because of the premium decrease, individuals who chose MA last year will be more likely to switch to a different MA insurer in the "Full Eq" counterfactual, compared with the "Partial Eq" counterfactual. Overall, the average premium across all insurers increase in both group of markets. In markets with larger advertising expenditures, the average monthly premium increases by about 11% from $19.5 to $21.6 (or from $234.0 to $259.2 annually). In markets with smaller advertising expenditures, the average monthly premium increases by about 2% from $41.5 to $42.5 (or from $498 to $510 annually).

The changes in market shares reported in Table 8 are consistent with the changes in premiums. Compared with the predicted changes in premiums, however, market shares will not decrease as much. The main reasons for this result for market shares are because a market share is a stock, as opposed to a flow, and because we calculate changes in market shares in a single year. Although advertising has a large impact on a new Medicare beneficiary's transition to MA as reported in Table 7, new Medicare beneficiaries are only a small fraction of the entire Medicare beneficiaries, most of whom face large switching cost. As a result, the effect of advertising on market shares in a single year will be limited in both counterfactual situations.

Shutting down advertising has qualitatively different effects on premiums depending on whether an insurer had a positive baseline advertising expenditure. First, insurers with positive baseline advertising expenditures will increase premiums because the fraction of unhealthy enrollees with such insurers will increase without advertising. In contrast, the other type of insurers will decrease premium because more healthy individuals enroll with them. In the baseline, insurers that advertised took away healthy

Table 8: Counterfactual: Market-Level Outcomes

		Markets with Small Ad			Markets with Large Ad		
		Baseline	Partial Eq	Full Eq	Baseline	Partial Eq	Full Eq
Insurers with Positive Ad	Average Monthly Premium ($)	37.1	37.1	39.3	20.6	20.6	28.8
	Average Market Share (%)	0.099	0.098	0.097	0.078	0.076	0.074
Insurers with Zero Ad	Average Monthly Premium ($)	45.1	45.1	45.1	18.6	18.6	15.0
	Average Market Share (%)	0.047	0.047	0.047	0.027	0.027	0.028
All Insurers	Average Monthly Premium ($)	41.5	41.5	42.5	19.5	19.5	21.6
	Average Market Share (%)	0.070	0.070	0.069	0.052	0.051	0.050

Note: Markets with Small Adv refers to a set of markets where market-level total advertising expenditures are below the median of market-level total advertising expenditures; Markets with Large Adv refers to a set of markets where market-level total advertising expenditures are above the median of market-level total advertising expenditures.

consumers at the expense of insurers with advertising. Therefore, shutting down the advertising leads to transfer of risk pools across insurers, which highlights a rent-seeking aspect of risk selection. The result implies that insurers can potentially engage in a wasteful advertising competition in order to take away healthy consumers. However, about 68% of insurers, who are mostly small in terms of market shares, did not have advertising expenditures in the data. It indicates that these insurers face high fixed costs of advertising. Thus, the extent of the wasteful competition was likely to limited.

It is important to recognize that changes in risk pools of insurers can impact premiums only when risk adjustment is imperfect. From (5), we can see that if risk adjustment were perfect, then $c_{jct}(z) - cap_{ct}(z)$ will be constant across z. On the other hand, if risk adjustment is imperfect, then an insurer's risk selection through advertising can result in a lower premium because an insurer will be able to construct a better risk pool by attracting healthier customers. Therefore, shutting down advertising may substantially increase premiums, which will potentially lower the consumer's welfare. To illustrate this point, we calculate the impact of shutting down advertising on consumer welfare, assuming advertising directly affects utility.[38] Table 22 in the Appendix shows the impact on consumer welfare depending on insurance status in the past year. Because we assume that advertising affects the utility directly, the welfare

[38]Note that whether advertising directly affects utility is non-trivial. Informative advertising can be welfare-improving, whereas persuasive advertising can be wasteful in terms of social welfare. The point of our exercise is to highlight the welfare impact of price change, which is investigated by comparing "Partial Eq" with "Full Eq."

Table 9: Counterfactual: Overpayment for MA Enrollees

	Markets with Small Ad			Markets with Large Ad			Markets with Any Ad		
	Baseline	Partial Eq	Full Eq	Baseline	Partial Eq	Full Eq	Baseline	Partial Eq	Full Eq
	Panel 1: Overpayment for Consumers That Are New to Medicare ($, per Month)								
Overpayment per MA enrollee ($)	113.8	112.9	113.0	106.6	98.1	96.7	109.1	103.4	102.6
Net Overpayment ($)	-15.3	-16.3	-16.1	10.3	1.8	0.4	-0.1	-5.8	-6.6
	Panel 2: Overpayment for all MA Enrollees ($, per Month)								
Overpayment per MA enrollee($)	151.7	151.5	151.5	155.9	154.0	154.0	154.5	153.2	153.2
Net Overpayment ($)	-2.3	-2.5	-2.5	9.9	8.0	8.1	5.3	4.0	4.0

decreases every group for "Partial Eq" counterfactual. The welfare decline is much larger under "Full Eq" than under "Partial Eq" because of the increase in premiums. Interestingly, individuals who had a MA plan in last year are negatively affected most because of the price increase. This is because they are more likely to choose an MA plan this year again due to switching cost.

Next, we investigate the effects of advertising on overpayment for an MA enrollee by the government. We define overpayment as the predicted capitation payment minus predicted Medicare reimbursement cost for the individual. Table 9 presents predicted overpayment for individuals who would choose MA in the baseline and counterfactual situations. Because MA insurers may receive overpayment even for enrolling an individual with the average health, we also report the amount of overpayment net of the amount of overpayment for enrolling an individual with the average health, which we call "net overpayment." We find that if advertising is shut down, then overpayment for overall MA enrollees will decrease because healthy consumers will be less likely to switch to MA without advertising. The change in the amount of overpayment is not very large and is smaller than the difference in the average premiums between the baseline and the "Full Eq" counterfactual. The result implies that the decrease in premiums resulting from advertising does not lead to too much government expenditures. Moreover, the effects of advertising on overpayment are much greater for individuals who are new to Medicare because of the larger effects of advertising on them. In fact, net overpayment for the new Medicare beneficiaries will be almost eliminated in the markets with relatively large advertising expenditures.

Lastly, we investigate the effects of advertising on the per-capita government expenditure. The total government expenditure is defined as the sum of capitation pay-

Table 10: Per-Capita Monthly Government Expenditures ($)

	Baseline	Partial Eq	Full Eq
Consumers That Are New to Medicare	307.4	304.9	304.2
All MA Enrollees	452.6	451.8	451.5

ments for MA enrollees and Medicare reimbursement costs for traditional Medicare enrollees. Table 10 shows that although advertising does not have a large effect for the overall population because of switching cost, shutting down advertising will decrease the expenditure by about 1% to $304.2 per individual per month among new Medicare beneficiaries. We also find that the difference in government expenditures between the baseline and the "Full Eq" counterfactual is smaller than the difference in the average premiums between the two situations, again implying that the decrease in premiums resulting from advertising does not lead to too much government expenditures.

In summary, we find that advertising mainly affects the demand for consumers who become newly eligible in Medicare, and at the same time, we find a substantial increase in premiums. These equilibrium impacts are often ignored when researchers are interested in measuring the welfare impact of risk selection under various risk adjustment systems, which so far emphasizes excess government expenditure due to risk selection (see Brown et al. 2014). Although a more complete welfare analysis is left to the future work, our results highlight that it is important to endogenize and quantify the risk selection tools of insurers in order to understand risk adjustment designs.[39]

8 Conclusion

This paper quantifies the impacts of advertising as risk selection on equilibrium market outcomes in MA. We first document evidence that both mass advertising and direct mail advertising are targeted in order to risk-select, attracting healthier individuals. In the main analysis, we develop and estimate an equilibrium model of the MA market with advertising in order to understand the impact of advertising on consumer demand. Our estimates demonstrate that advertising has positive effects on overall demand, but

[39] An important reason we did not attempt to conduct a complete welfare analysis is that such an analysis with advertising heavily depends on how we specify the way advertising affects individual utility. For example, informative advertising can be welfare-improving, whereas persuasive advertising can be wasteful in terms of social welfare.

a much larger effect on the demands of the healthy. Then, we conduct a counterfactual experiment that shuts down advertising to quantitatively evaluate the importance of risk selection through advertising on market outcomes. We find that the equilibrium premium increases on average up to 40% for insurers that had relatively large advertising expenditures, as their risk pools deteriorate. Although we find that risk selection through advertising has a rent-seeking aspect, it did not likely lead to a wasteful advertising competition. Therefore, risk selection through advertising may make consumers better off by lowering premiums without much inefficient spending.

An important future work is to quantify the welfare impact of risk selection and investigate the optimal design of risk adjustment. The main challenge in our context is to develop a coherent framework in which to measure the impact of advertising on consumer welfare. This requires an explicit modeling and identification of various mechanisms of the impact of advertising, for example informative, persuasive, and signaling roles, which are known to be challenging. Another important avenue is to consider other instruments for conducting risk selection. These extensions will allow us to conduct a more complete welfare assessment of risk selection.

References

Ackerberg, D. A., 2001. Empirically distinguishing informative and prestige effects of advertising. RAND Journal of Economics, 316–333.

Ackerberg, D. A., 2003. Advertising, learning, and consumer choice in experience good markets: an empirical examination. International Economic Review 44 (3), 1007–1040.

Batata, A., 2004. The effect of hmos on fee-for-service health care expenditures: Evidence from medicare revisited. Journal of health economics 23 (5), 951–963.

Bauhoff, S., 2012. Do health plans risk-select? an audit study on germany's social health insurance. Journal of Public Economics 96 (9), 750–759.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. Econometrica, 841–890.

Berry, S., Levinsohn, J., Pakes, A., 2004. Differentiated products demand systems from a combination of micro and macro data: The new car market. Journal of Political Economy 112 (1), pp. 68–105.

Brown, J., Duggan, M., Kuziemko, I., Woolston, W., 2014. How does risk selection respond to risk adjustment? new evidence from the medicare advantage program. American Economic Review 104 (10), 3335–64.

Brown, J. R., Goolsbee, A., 2002. Does the internet make markets more competitive? evidence from the life insurance industry. Journal of Political Economy 110 (3), pp. 481–507.

Cabral, M., Geruso, M., Mahoney, N., 2014. Does privatized health insurance benefit patients or producers? evidence from medicare advantage. Working Paper 20470, National Bureau of Economic Research.

Cebul, R. D., Rebitzer, J. B., Taylor, L. J., Votruba, M. E., 2011. Unhealthy insurance markets: Search frictions and the cost and quality of health insurance. The American Economic Review 101 (5), 1842–71.

Chiappori, P.-A., Salanie, B., 2000. Testing for asymmetric information in insurance markets. Journal of political Economy 108 (1), 56–78.

Ching, A. T., Ishihara, M., 2012. Measuring the informative and persuasive roles of detailing on prescribing decisions. Management Science 58 (7), 1374–1387.

Clark, C. R., Doraszelski, U., Draganska, M., 2009. The effect of advertising on brand awareness and perceived quality: An empirical investigation using panel data. Quantitative Marketing and Economics 7 (2), 207–236.

Curto, V., Einav, L., Levin, J., Bhattacharya, J., 2014. Can health insurance competition work? evidence from medicare advantage. Working Paper 20818, National Bureau of Economic Research.

Decarolis, F., Guglielmo, A., 2015. Insurers response to selection risk: Evidence from medicare enrollment reforms. SIEPR Working Paper 15-030.

Decarolis, F., Polyakova, M., Ryan, S. P., 2015. The welfare effects of supply-side regulations in medicare part d. Working Paper 21298, National Bureau of Economic Research.

Dubois, P., Griffith, R., O'Connell, M., 2014. The effects of banning advertising in junk food markets. Unpublished manuscript, Toulouse School of Economics.

Duggan, M., Starc, A., Vabson, B., 2014. Who benefits when the government pays more? pass-through in the medicare advantage program. Working Paper 19989, National Bureau of Economic Research.

Ellis, R. P., Fernandez, J. G., 2013. Risk selection, risk adjustment and choice: Concepts and lessons from the americas. International Journal of Environmental Research and Public Health 10 (11), 5299–5332.

Fang, H., Keane, M. P., Silverman, D., 2008. Sources of advantageous selection: Evidence from the medigap insurance market. Journal of Political Economy 116 (2), pp. 303–350.

Finkelstein, A., McGarry, K., 2006. Multiple dimensions of private information: evidence from the long-term care insurance market. American Economic Review 96 (4), 938–958.

Geruso, M., Layton, T., 2015. Upcoding: Evidence from medicare on squishy risk adjustment. Working Paper 21222, National Bureau of Economic Research.

Goeree, M. S., 2008. Limited information and advertising in the us personal computer industry. Econometrica 76 (5), 1017–1074.

Gordon, B. R., Hartmann, W. R., 2013. Advertising effects in presidential elections. Marketing Science 32 (1), 19–35.

Handel, B. R., 2013. Adverse selection and inertia in health insurance markets: When nudging hurts. American Economic Review 103 (7), 2643–82.

Hastings, J. S., Hortaçsu, A., Syverson, C., 2013. Advertising and competition in privatized social security: the case of mexico.

Hausman, J. A., 1996. Valuation of new goods under perfect and imperfect competition. In: The economics of new goods. University of Chicago Press, pp. 207–248.

Ho, K., Hogan, J., Morton, F. S., 2015. The impact of consumer inattention on insurer pricing in the medicare part d program. Working Paper 21028, National Bureau of Economic Research.

Imbens, G. W., Lancaster, T., 1994. Combining micro and macro data in microeconometric models. The Review of Economic Studies 61 (4), 655–680.

Kuziemko, I., Meckel, K., Rossin-Slater, M., 2013. Do insurers risk-select against each other? evidence from medicaid and implications for health reform. NBER Working Paper (w19198).

Langwell, K. M., Hadley, J. P., 1989. Evaluation of the medicare competition demonstrations. Health Care Financing Review 11 (2), 65.

Lustig, J., 2011. Measuring welfare losses from adverse selection and imperfect competition in privatized medicare. Manuscript.

Mehrotra, A., Grier, S., Dudley, R. A., 2006. The relationship between health plan advertising and market incentives: Evidence of risk-selective behavior. Health Affairs 25 (3), 759–765.

Mello, M. M., Stearns, S. C., Norton, E. C., Ricketts, T. C., 2003. Understanding biased selection in medicare hmos. Health services research 38 (3), 961–992.

Miller, K., 2014. Do private medicare firms face lower costs? Unpublished manuscript, University of Minnesota.

Miller, K., Petrin, A., Town, R., Chernew, M., 2014. Health plan changes in response to medicare advantage payment rates. Unpublished manuscript, University of Minnesota.

Moshary, S., 2015. Price discrimination across pacs and the consequences of political advertising regulation. Unpublished manuscript, MIT.

Neuman, P., Maibach, E., Dusenbury, K., Kitchman, M., Zupp, P., 1998. Marketing hmos to medicare beneficiaries. Health Affairs 17 (4), 132–139.

Nevo, A., 2001. Measuring market power in the ready-to-eat cereal industry. Econometrica 69 (2), 307–342.

Newhouse, J. P., Price, M., Huang, J., McWilliams, J. M., Hsu, J., 2012. Steps to reduce favorable risk selection in medicare advantage largely succeeded, boding well for health insurance exchanges. Health Affairs 31 (12), 2618–2628.

Newhouse, J. P., Price, M., McWilliams, J. M., Hsu, J., McGuire, T., March 2014. How much favorable selection is left in medicare advantage? (20021).

Nosal, K., 2012. Estimating switching costs for medicare advantage plans. Unpublished manuscript, University of Mannheim.

Polyakova, M., 2014. Regulation of insurance with adverse selection and switching costs: Evidence from medicare part d. Unpublished manuscript, Stanford University.

Pope, G. C., Kautter, J., Ellis, R. P., Ash, A. S., Ayanian, J. Z., Ingber, M. J., Levy, J. M., Robst, J., et al., 2004. Risk adjustment of medicare capitation payments using the cms-hcc model.

Starc, A., 2014. Insurer pricing and consumer welfare: evidence from medigap. The RAND Journal of Economics 45 (1), 198–220.

Town, R., Liu, S., 2003. The welfare impact of medicare hmos. RAND Journal of Economics, 719–736.

Van de Ven, W. P., Ellis, R. P., 2000. Risk adjustment in competitive health plan markets. Vol. 1, Part A of Handbook of Health Economics. Elsevier, pp. 755 – 845.

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A Appendix

A.1 Incentives for Risk Selection

Using the data available in this paper, we investigate whether MA insurers have incentives to risk-select by calculating potential expected profits from enrolling a healthy and an unhealthy individual. Although recent papers make use of an individual's risk score (e.g., Brown et al. 2014 and Curto et al. (2014)), we do not have access to such information with our data. However, the MCBS still provides useful information that can shed light on potential profits for insurers from enrolling individuals of different health types. We make use of the two variables in the MCBS in order to calculate the potential profits from a healthy and an unhealthy individual. First, the MCBS contains information on how much an MA insurer received for enrolling an individual included in the data. Second, we use the amount of Medicare reimbursement costs for individuals enrolled in traditional Medicare.

A possible measure of potential profit for an individual is the difference between the expected capitation payment if the individual enrolls in MA and the expected Medicare reimbursement cost if the individual enrolls in traditional Medicare. However, an important limitation of the two variables is that they are non-missing only for individuals depending on their insurance choice. Therefore, we impute the expected capitation payment and the expected Medicare reimbursement cost using their relationship with an individual's observed characteristics, which is estimated with individuals who have non-missing values for the two variables.

For the capitation payment, we run the following regression using information from individuals who enrolled in MA:

$$cp_{it} = f(Age_{it}, Female_{it}, Health_{it}, Benchmark_{county(i),t})\beta + \varepsilon_{it}, \tag{6}$$

where cp_{it} denotes the amount of the monthly capitation payment for individual i and year t, and $f(Age_{it}, Female_{it}, Health_{it}, Benchmark_{county(i),t})$ is a function that generates interactions between an individual's age, gender, health status, and the capitation benchmark of the individual's county in year t ($Benchmark_{county(i),t}$). An individual health status $Health_{it}$ is a binary variable that is equal to one if individual i is healthy as defined when we described the MCBS in Section 2. Because of the introduction of the new risk adjustment regime in 2004, the relationship between cp_{it} and $f(Age_{it}, Female_{it}, Health_{it}, Benchmark_{county(i),t})$ may have changed during the year. Thus, we run separate regressions for the years before 2004 and after 2003. The regression results are reported in Table 15 in the Appendix. Using the estimates, we simulate the expected capitation payment for each individual included in the MCBS.

For the expected Medicare reimbursement cost, we run a similar regression using information from individuals who enrolled in traditional Medicare:

$$mr_{it} = f(Age_{it}, Female_{it}, Health_{it}, Cost_{county(i),t})\beta + \varepsilon_{it}, \tag{7}$$

where mr_{it} denotes the Medicare reimbursement cost for individual i in year t averaged over twelve months, and $f(Age_{it}, Female_{it}, Health_{it}, Cost_{county(i),t})$ is a function that generates interactions between an individual's age, gender, health status, and per-capita Medicare reimbursement cost in the individual's county in year t ($Cost_{county(i),t}$). Note that information for $Cost_{county(i),t}$ does not come from the MCBS but directly from the CMS. Thus, $Cost_{county(i),t}$ is the exact per-capita Medicare cost for the county in year t. The regression results are reported in Table 16 in the Appendix. Using the estimates, we simulate the expected Medicare reimbursement cost for each individual included in the MCBS.

Once we calculate the expected capitation payment and Medicare cost for each individual in the MCBS, we calculate the potential profit for an MA insurer from enrolling each individual. The potential profit π_{it} is defined as

$$\pi_{it} = E[cp_{it}] - E[mr_{it}].$$

Table 11 presents the average monthly potential profits depending on an individual's health status before and after the introduction of the more comprehensive risk adjustment regime after 2003. Note that the potential profit from a healthy individual is substantially larger than that from an unhealthy individual, regardless of risk adjustment regimes. The differences between the potential profits from a healthy and an unhealthy

Table 11: Incentives to Target Healthy Consumers

	$E[\pi_{it}\|Health_i = 1]$ ($)	$E[\pi_{it}\|Health_i = 0]$ ($)	Difference ($)
Before 2004	214.4	-303.8	518.2
After 2003	252.4	-214.2	466.6

individual are $518.2 and $466.4 before and after the new risk adjustment regime, respectively. Although $E[\pi_{it}|Health_i = 1]$ increased after 2003, $E[\pi_{it}|Health_i = 0]$ increased even more, and the difference decreased after 2003. Therefore, we find that enrolling healthy individuals is much more profitable for MA insurers before and after the new risk adjustment regime, although relative potential profits from healthy individuals slightly decreased after 2003.

The fact that we find that enrolling healthy individuals continues to be profitable even after 2003 may seem inconsistent with the finding that the new risk adjustment regime substantially reduces the capitation payment to individuals with low risk scores, who are considered healthier according to the risk score system (see Table 3 in Brown et al. (2014)). However, we argue that our finding is not necessarily contradictory to the finding by Brown et al. (2014) for two reasons. First, they also find that the new risk adjustment regime still does not account for Medicare costs for unhealthy individuals. In other words, the capitation payment for an individual with a lower risk score is still greater than the individual's expected Medicare cost. In fact, Brown et al. (2014) find that for 77% of individuals, the capitation payments are estimated to be larger than their expected Medicare costs before and after the new risk adjustment regime. Because $Health_{it}$ is equal to one for about 83% of individuals as shown in Table 2, it is likely that overall, healthy individuals overall continue to result in greater profits for MA insurers. Second, the capitation benchmark increased when the new risk adjustment regime was introduced after 2003. As a result, the capitation payment for every individual increased, although the relative capitation payment changed.

A.2 Direct Mail Advertising

This section provides a supplemental analysis using the direct mail advertising. Although mass advertising can be targeted more at geographical levels, the direct mail advertising can be used to target certain individuals. We study whether advertising is targeted and whether those target advertising leads to actual demand.

The dataset is from Mintel Comperemedia (Mintel henceforth), which is a database tracking direct mail advertising in the United States. In each month, the database collects direct mailings from nationally representative households throughout the United States. These households are asked to collect and return mailings in the eight sectors monitored by Mintel, which include health insurance. The Mintel data contain information on each mailing such as the advertiser and product name, which allows us to tell whether a mailing is advertising an MA plan. Moreover, the data also provide information of demographic characteristics of the recipient of each mailing such as ages of household heads, household income, zip code, and so on. Based on the income measure provided in the Mintel data, we also created a new income variable using the five categories that were used to create a new income variable for individuals in the MCBS. For our analysis, we excluded individuals from counties where there is no MA insurer available. Moreover, we selected households with at least one household head who is at least 64.[40]

A.2.1 Summary Statistics

Table 12 presents summary statistics from Mintel. In this data set, the unit of observation is a combination of individual and month, meaning that an individual received 0.158 mailings from MA plans on average. Conditional on receiving at least one MA-related mailing, an individual received 1.24 mailings on average. We find that those who received mailings tend to have lower household income and also reside in neighborhoods with lower average income (measured by zip-code-level).[41] Those who received mailings tend to be older than those who did not. Moreover, individuals in markets with more Medicare beneficiaries are more likely to receive mailings.

[40]We chose age 64 as the threshold because an individual can enroll in MA three months before they turn 65. Thus, MA insurers are likely to send direct-marketing mail to 64-year-old individuals as well as to older individuals.

[41]We obtain the zip-code-level mean income from the IRS,which is available at www.irs.gov/uac/SOI-Tax-Stats-Individual-Income-Tax-Statistics-Zip-Code-Data-(SOI).

Table 12: Mintel Summary Stats

	Households w/o MA Mails	Households w/ MA Mails	Overall
Number of MA Mailings	0	1.24	0.16
Income = 1 (%) (lowest)	17.0	20.7	17.4
Income = 2 (%)	16.3	20.5	16.8
Income = 3 (%)	15.6	16.7	15.8
Income = 4 (%)	16.1	15.7	16.0
Income = 5 (%) (highest)	35.0	26.5	33.9
Zip code-Level Income ($)	48,662	47,381	48,500
Age of Female Household Head if Any	67.7	71.3	68.2
Age of Male Household Head if Any	69.4	72.5	69.8
Number of Medicare Beneficiaries (County Level)	163,725	219,626	170,849
Observations	14,515	2,120	16,635

A.2.2 Evidence on Targeting and Its Impact on Demand

Although we find evidence that mass advertising is targeted based on the profitability of each county, insurers may further implement sophisticated targeting within a county. To pursue this possibility, we investigate the second measure of advertising: direct mail advertising. We believe that direct mailings are very useful tools from an insurer's perspective for targeting its advertising at an individual with certain characteristics. Presumably, insurers often have access to the demographic characteristics of individuals who live at specific addresses or have access to information about the average demographic in a small geographic area such as zip code. Therefore, they may utilize sophisticated targeting to attract less costly customers. By using this data set, we can gain insights into which individuals are more likely to receive advertising.

We first investigate whether the targeting of direct mailings responded to the introduction of the comprehensive risk adjustment in 2004. As discussed earlier, Brown et al. (2014) find that capitation payments for individuals with lower risk scores substantially decreased after the new risk adjustment regime. Thus, although enrolling a healthy individual continues to be profitable to in the new regime, profitability from an individual with a lower risk score likely decreased compared with that from an individual with a higher risk score. The targeting of direct mailings was then likely to change with the introduction of the new regime.

One limitation of the Mintel data is that we do not observe health-related measures for individuals. Thus, we use a household's income as a proxy for the risk scores of the household's heads, which is motivated by the fact that an individual's health and income are highly negatively correlated. We use two different measures for income. In the first specification, we use an individual's income reported in the Mintel data, which is a categorical variable with five categories as mentioned before. In the second specification, we use the average income in an individual's zip code.

With the first specification, we run the following regression:

$$y_{it} = \alpha_0 + \sum_{k=1}^{4} \alpha_{1,k} \mathbf{1}[I_{it} = k] + \sum_{k=1}^{4} \alpha_{2,k} \mathbf{1}[t \geq Oct\,2003] \mathbf{1}[I_{it} = k] + X_{it}\beta + f_t + f_{c(i),risk(t)} + \varepsilon_{it} \quad (8)$$

where y_{it} is the number of MA-related direct mailings that household i received in a particular month-year t, I_{it} is a categorical variable for a household income measure, which takes a higher value if an income is higher, and $\mathbf{1}[I_{it} = k]$ is a dummy variable that is equal to one if I_{it} is equal to k. As mentioned earlier, I_{it} has five categories from one to five, with a higher number assigned for a greater income. In (8), we normalize coefficients for the highest income to zero. That is, $\alpha_{1,5} = \alpha_{2,5} = 0$. Similarly, $\mathbf{1}[t \geq Oct, 2003]$ is a dummy variable that is equal to one for a time in or after October 2003. We chose the beginning of the fourth quarter of 2003 as the time when the new risk adjustment regime starts to affect an MA insurer's targeting. Because its implementation was announced in March 2003, MA insurers likely adjusted their targeting even before the beginning of 2004. Moreover, X_{it} is a vector of other characteristics of a household i, including whether there is a male or female household head, ages of male and female household heads if they exist, potential average profit defined as the capitation benchmark minus the fee-for-service cost for each county-year, the number of Medicare beneficiaries in each county-year, and median household income for each county-year. Next, f_t represent fixed effects for month-year t. In addition, $f_{c(i),risk(t)}$ represent fixed effects for a combination of household i's county of residence and risk adjustment regime. As discussed before, if $t < Oct\,2003$, then the time belongs to the old risk adjustment regime. And if $t \geq Oct\,2003$, then the time belongs to the new risk adjustment regime. Thus, each county has two fixed effects in this regression.

In (8), our main coefficients of interest are $\alpha_{2,k}$ for $k = 1, \cdots, 4$. This measures how the change in risk adjustment in 2004 affected an insurer's incentives to target households with different incomes, relative to the pre-2004 period. Because $\alpha_{2,5} = 0$ by normalization, coefficient $\alpha_{2,k}$ for $k = 1, \cdots, 4$ measures how many mailings a household whose I_{it} is equal to k received, compared with a household whose I_{it} is equal to 5 (i.e., the highest income category group) after the new risk adjustment regime. Note that because of the fixed effects included in the regression, we are not relying on a cross-county variation, meaning that identification of α_{2k} does not come from cross-county variation in potential profits. Instead, the identification uses within-county variation in incentives to target different individuals before and after the policy change.

A legitimate concern about using household income as a proxy for health risk is that income may be correlated with other unobserved heterogeneity that can have an impact on a household's medical expenditures. This is important because an insurer's profit will eventually depend on medical expenditures instead of health status itself. For example, an individual with a higher income may have a higher willingness to pay for medical care, which may result in a greater medical expenditure. Therefore, coefficient estimates $\alpha_{1,k}$ for $k = 1, \cdots, 4$ will not provide good information about whether MA insurers target healthy individuals. However, we are interested in relative changes in targeting induced by the policy change, which are captured by α_{2k}. As long as the relationship between the unobserved heterogeneity and income does not change at the time when the new risk adjustment design was introduced, the concern will not apply to α_{2k}.

With the second specification, we estimate the following equation:

$$y_{it} = \alpha_0 + \alpha_{1,zip} I_{zip(i),t} + \alpha_{2,zip} \mathbf{1}[t \geq Oct, 2003] I_{zip(i),t} + X_{it}\beta + f_t + f_{c(i),risk(t)} + \varepsilon_{it} \qquad (9)$$

where $I_{zip(i),t}$ represents the average income in the zip code of individual i's address at time t. Here, the coefficient of interest is $\alpha_{1,zip}$. The concern about the unobserved heterogeneity also applies to this specification as well and can be addressed with the same argument put forth in the previous paragraph.

The results are summarized in columns (1) and (2) in Table 13, which present the results with household income and zip-code income, respectively. The results show that lower-income households are more likely to receive advertising after the new risk adjustment regime in both specifications. In the first specification, we find that the number of mailings will increase the most under the new regime for households with incomes that are not too low or too high, which is consistent with the previous finding

Table 13: Targeting with Direct Mail Advertising

	(1)	(2)		(3)	(4)
Dependent variable:	# of MA mails		Dependent variable:	Switches to MA	
$I_{zip(i),t}$		-0.000105	$I_{zip(i),t}$		-0.000126*
$\mathbf{1}[t \geq Oct, 2003]I_{zip(i),t}$		-0.000679**	$\mathbf{1}[t \geq 2004]I_{zip(i),t}$		-2.44e-05
$\mathbf{1}[I_{it} = 1]$ (lowest)	0.00326		$\mathbf{1}[I_{it} = 1]$ (lowest)	0.00965	
$\mathbf{1}[I_{it} = 2]$	0.00906		$\mathbf{1}[I_{it} = 2]$	0.0262***	
$\mathbf{1}[I_{it} = 3]$	-0.00451		$\mathbf{1}[I_{it} = 3]$	0.0223***	
$\mathbf{1}[I_{it} = 4]$ (2nd highest)	-0.0117		$\mathbf{1}[I_{it} = 4]$ (2nd highest)	0.0155**	
$\mathbf{1}[t \geq Oct, 2003]\mathbf{1}[I_{it} = 1]$	0.0433*		$\mathbf{1}[t \geq 2004]\mathbf{1}[I_{it} = 1]$	-0.0118	
$\mathbf{1}[t \geq Oct, 2003]\mathbf{1}[I_{it} = 2]$	0.0177		$\mathbf{1}[t \geq 2004]\mathbf{1}[I_{it} = 2]$	-0.00398	
$\mathbf{1}[t \geq Oct, 2003]\mathbf{1}[I_{it} = 3]$	0.0857***		$\mathbf{1}[t \geq 2004]\mathbf{1}[I_{it} = 3]$	-0.00201	
$\mathbf{1}[t \geq Oct, 2003]\mathbf{1}[I_{it} = 4]$	0.0632**		$\mathbf{1}[t \geq 2004]\mathbf{1}[I_{it} = 4]$	-0.00315	
Other Covariates	Yes	Yes	Other Covariates	Yes	Yes
County-Risk Adjustment Regime FE	Yes	Yes	County-Risk Adjustment Regime FE	Yes	Yes
Year-Month FE	Yes	Yes	Year-Month FE	Yes	Yes
Observations	13,430	13,317	Observations	21,836	21,448
Data Source	Mintel		Data Source	MCBS	

that it is still unprofitable to enroll individuals with very high risk scores. When a zip-code income is used, we find that insurers tend to send more mailings to a lower-income neighborhood under the new regime. Moreover, we do not find any statistically significant patterns in targeting before the new regime in either specification.

Although we find that insurers target individuals with different characteristics after the new regime, it does not necessarily mean that an individual's demand for MA responded to the different targeting. Because the Mintel data do not provide any information about an individual's insurance choice, we cannot directly test whether the change in the targeting of direct mailings led to a consistent change in demand for MA. Instead, we test the hypothesis indirectly using the MCBS. Specifically, we investigate whether an individual, with characteristics targeted by MA insurers, is (i) more likely to switch to MA if the individual did not choose MA last year or (ii) more likely to switch to a different MA insurers if the individual chose an MA insurer last year.[42]

Now we define y_{it} to be a dummy variable that equals one if condition (i) or (ii) is met. We run regressions similar to equations (8) and (9). Specifications (3) and (4) in Table 13 presents results from the two regressions. Note that none of the estimated

[42] Therefore, this approach is similar to that in Brown and Goolsbee (2002), who investigate the impact of Internet access on life insurance enrollment.

coefficients for the interactions between incomes and the new risk adjustment regime are statistically significant. This result implies that direct mail was not very effective in inducing consumers to enroll in MA at least for the years considered in our analysis. Because the cost of sending direct mailings is very tiny, insurers likely responded to the change in the risk adjustment regime, expecting that direct mailings to newly targeted individuals will lead to a greater demand by them. Eventually, however, any changes in demand were quantitatively insignificant.

A.3 Details on the Supply Side

A.3.1 Estimation of the Expected Health Costs

We assume that an MA enrollee's realized health reimbursement cost for insurer *jct* is given by

$$\ln\left(1+m(z_i, x_{jct}, \omega_{ijct}; \lambda)\right) = z_i\lambda_z + x_{jct}\lambda_x + \lambda_w\omega_{ijct}$$

where ω_{ijct} is assumed to be a standard normal random variable.

The realized reimbursement cost for an MA's enrollee in a given year is available from the MCBS Cost and Use module. Because we observed an individual's characteristics z_i and those of the insurer the individual chose x_{jct}, estimating parameter λ is straightforward and can be done independently of the demand model. Table 14 presents estimates for λ.

A.3.2 Solving for η_{jct}

The profit function (5) will lead to the first order condition for the optimal pricing as follows:

$$\eta_{jct} = \frac{Q_{jct} + \int_{z_i}\left(p_{jct} + cp(z_i) - E_\omega[m(z_i, x_{jct}, \omega_{ijct}; \lambda)]\right)\frac{\partial q_{jct}(z)}{\partial p_{jct}} dF_{ct}(z_i)}{\frac{\partial Q_{jct}}{\partial p_{jct}}}. \quad (10)$$

Because parameter λ can be estimated outside the demand model and because both $\frac{\partial q_{jct}(z)}{\partial p_{jct}}$ and $\frac{\partial Q_{jct}}{\partial p_{jct}}$ can be calculated based on parameter estimates for the demand model, η_{jct} can be calculated using equation (10) by assuming observed premiums in the data are at equilibrium.

A.4 Tables

Table 14: Estimates for Health Reimbursement Costs

VARIABLES	Co eff	Std. Error
h_{it}	-1.048***	(0.0674)
Age	0.420***	(0.0812)
Age^2	-0.00262***	(0.000516)
$Female$	0.234***	(0.0524)
Per-Capita Medicare Reimbursement Costs in County-Year	0.00121***	(0.000240)
Copay for 10 Inpatient Days	-1.36e-05	(5.26e-05)
Copay for 20 Days at Skilled Nursing Facility	-0.000161***	(6.16e-05)
Coinsurance for 20 Days at Skilled Nursing Facility	0.210***	(0.0276)
Copay for Specialist Visit	-0.00420	(0.00273)
Copay for Primary Care Physician Visit	-0.0244***	(0.00600)
Coinsurance for Specialist Visit	-0.0888*	(0.0486)
Coinsurance for Primary Care Physician Visit	-0.177	(0.185)
Dummy: Dental Coverage	-0.249***	(0.0848)
Dummy: Hearing Exam	0.561**	(0.251)
Dummy: Hearing Aid	0.0453	(0.0633)
Dummy: Routine Eye Exam	0.300***	(0.0914)
Dummy: Drug Coverage	0.154**	(0.0645)
Dummy : HMO	0.0586	(0.556)
Dummy: PPO	-1.388**	(0.566)
Dummy: Private Fee for Service	-1.016	(0.709)
Observations	4,890	
R-squared	0.097	

Note 1: The variable “Copay for 10 Inpatient Days” refers to the amount of copayments when a patient stays 10 days at an inpatient facility. Other variables with similar formats can be interpreted in a similar way.

Note 2: In addition to the variables included in the table, we also included variable dummy variables for insurers with missing information in each benefit. For example, some insurers have a coinsurance for a specialist visit instead of a copayment. In this case, we included a dummy variable that equals to one if information about copayment does not exist.

Table 15: Capitation Payments for MA Enrollees

	Before 2004		After 2004	
VARIABLES	Coeff	Std Err	Coeff	Std Err
$1[Health_{it}=1]$	-3,040	(3,539)	-2,318	(4,549)
$1[Health_{it}=1]\times Age$	-11.74	(15.88)	-51.74	(32.55)
$1[Health_{it}=0]\times Age$	-86.87	(87.70)	-119.5	(115.5)
$1[Health_{it}=1]\times Age^2$	0.0856	(0.102)	0.350*	(0.210)
$1[Health_{it}=0]\times Age^2$	0.550	(0.550)	0.832	(0.758)
$1[Health_{it}=1]\times Benchmark$	-5.516***	(1.082)	-7.350***	(2.011)
$1[Health_{it}=0]\times Benchmark$	-9.376*	(5.521)	-9.524	(7.292)
$1[Health_{it}=1]\times Age\times Benchmark$	0.148***	(0.0279)	0.197***	(0.0520)
$1[Health_{it}=0]\times Age\times Benchmark$	-0.000809***	(0.000179)	-0.00114***	(0.000333)
$1[Health_{it}=1]\times Age^2\times Benchmark$	0.244*	(0.140)	0.267	(0.191)
$1[Health_{it}=0]\times Age^2\times Benchmark$	-0.00141	(0.000879)	-0.00167	(0.00124)
$Female$	16.45	(12.01)	5.777	(21.12)
$Female\times Benchmark$	-0.169***	(0.0206)	-0.156***	(0.0349)
Observations	6,258		2,592	

*** p<0.01, ** p<0.05, * p<0.1

Note: The sample for this analysis consists of individuals in the MCBS who chose MA.

Table 16: Reimbursement Costs for Traditional Medicare Enrollees

	Before 2004		After 2004	
VARIABLES	Coeff	Std Err	Coeff	Std Err
$1[Health_{it}=1]$	1,666	(2,327)	-5,824*	(3,027)
$1[Health_{it}=1]\times Age$	71.88***	(12.97)	44.36**	(21.52)
$1[Health_{it}=0]\times Age$	106.2*	(57.72)	-102.0	(74.30)
$1[Health_{it}=1]\times Age^2$	-0.407***	(0.0829)	-0.212	(0.137)
$1[Health_{it}=0]\times Age^2$	-0.621*	(0.367)	0.708	(0.472)
$1[Health_{it}=1]\times Cost$	0.547***	(0.105)	0.698***	(0.145)
$1[Health_{it}=0]\times Cost$	2.180***	(0.278)	1.470***	(0.370)
$Female$	34.00	(65.91)	174.9*	(95.80)
$Female\times Cost$	-0.194	(0.147)	-0.419**	(0.192)
Observations	23,890		12,058	

*** p<0.01, ** p<0.05, * p<0.1

Note: The sample for this analysis consists of individuals in the MCBS who stayed with traditional Medicare.

Table 17: Correlation between Mean and Variance of Health Expenditures

Dependent Variable	Medicare Reimbursement Cost			
	(1)		(2)	
	Coefficient	Std. Error	Coefficient	Std. Error
$\mathbf{1}[Health_{it} = 0]$	-61.85	(156.7)	-35.28	(158.3)
Age	-8.837	(5.714)	-10.43*	(5.804)
Dummy: Female?	106.4	(81.03)	135.5*	(82.26)
Per-Capita Medicare Cost	-2.229**	(0.872)	-2.753***	(1.063)
$\mathbf{1}[Health_{it} = 0] \times$ Per-Capita Medicare Cost	1.140***	(0.311)	1.094***	(0.313)
Age $\times$ Per-Capita Medicare Cost	0.0373***	(0.0115)	0.0406***	(0.0117)
Female $\times$ Per-Capita Medicare Cost	-0.307*	(0.162)	-0.363**	(0.165)
Year FE?	Yes		Yes	
County FE?	No		Yes	
Observations	16,525		16,525	
R-squared	0.070		0.095	

*** p<0.01, ** p<0.05, * p<0.1

Note: The sample for this analysis consists of individuals in the MCBS who stayed with traditional Medicare.

Table 18: Geographical Targeting of Mass Advertising

VARIABLES	Coeff	SE	Coeff	SE
1[year>=2004] $\times$64-65 population	0.133***	(0.0220)	0.137***	(0.0246)
64-65 Population	-0.144***	(0.0361)	-0.555***	(0.0539)
Population	0.0138***	(0.00230)	0.0132***	(0.00415)
Capitation Benchmark	5.733***	(0.512)	2.996***	(0.555)
FFS cost	-1.209***	(0.420)	-0.901**	(0.424)
Number of Insurers	-16.79*	(9.681)	-144.3***	(24.96)
1[year>=2004] $\times$ population	-0.0105***	(0.00232)	-0.0141***	(0.00267)
1[year>=2004] $\times$Capitation Benchmark	0.458	(0.425)	0.222	(0.443)
1[year>=2004] $\times$FFS cost	1.134***	(0.368)	0.461	(0.382)
1[year>=2004] $\times$Number of Insurers	48.49***	(9.579)	-13.65	(12.09)
Capitation Benchmark$\times$64-65 population			0.000548***	(8.60e-05)
Capitation Benchmark$\times$ population			1.24e-05	(1.00e-05)
Capitation Benchmark$\times$Number of Insurers			0.0604	(0.0645)
FFS cost $\times$64-65 population			-0.000262***	(5.77e-05)
FFS cost $\times$ population			1.89e-06	(6.62e-06)
FFS cost $\times$Number of Insurers			0.213***	(0.0499)
Observations	9,065		9,065	
R-squared	0.657		0.672	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 19: Health and Problems with Vision and Hearing

Dependent Var	Vision Status 1		Vision Status 2		Hearing Status 1		Hearing Status 2	
	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err
$\mathbf{1}[Health_{it} = 0]$	0.203***	(0.0146)	0.146***	(0.0330)	0.130***	(0.0129)	0.0967***	(0.0293)
Age	-0.0594***	(0.0145)	-0.147***	(0.0262)	-0.0611***	(0.0125)	-0.0763***	(0.0228)
Age Squared	0.000449***	(9.34e-05)	0.00104***	(0.000167)	0.000487***	(8.02e-05)	0.000524***	(0.000147)
Observations	21,734		5,057		21,811		6,329	

*** p<0.01, ** p<0.05, * p<0.1

Note 1: Vision Status 1 = a categorical variable that describes an individual's status of vision with a higher number representing more serious problems with one's vision.
Note 2: Vision Status 2 = a categorical variable that describes how difficult an individual to find out about Medicare due to a problem with vision. This variable is populated only for individuals that indicated that they had problems with vision for Vision Status 1. And this variable became available from 2002.

Note 3: Hearing Status 1 and 2 are defined in a similar way. And Hearing Status 2 also became available from 2002.

Table 20: Estimates for Parameters in Mean Utility (δ_{jmt})

VARIABLES	Coefficient	Std Error
Premium	-0.0146**	(0.00606)
$\ln\left(1+ad_{jm(c)t}\right)$	-0.546**	(0.268)
Dummy: Drug Coverage	0.358***	(0.0878)
Copay per Inpatient Stay	0.000488	(0.000383)
Copay for 10 Inpatient Days	0.000112	(0.000160)
Copay for 40 Inpatient Days	-0.000218	(0.000137)
Copay for 90 Inpatient Days	9.10e-05*	(5.00e-05)
Copay per Stay at Skilled Nursing Facility	0.000285	(0.000193)
Copay for 5 Days at Skilled Nursing Facility	0.000373	(0.000622)
Copay for 20 Days at Skilled Nursing Facility	0.000165	(0.000227)
Copay for 50 Days at Skilled Nursing Facility	-9.36e-05*	(5.47e-05)
Copay for Specialist Visit	2.57e-05	(0.00494)
Copay for Primary Care Physician Visit	-0.0431***	(0.0107)
Coinsurance per Inpatient Stay	-0.0350	(0.0621)
Coinsurance per Stay at Skilled Nursing Facility	-0.786	(0.612)
Coinsurance for 20 Days at Skilled Nursing Facility	-0.766	(0.713)
Coinsurance for 100 Days at Skilled Nursing Facility	0.236	(0.210)
Coinsurance for Specialist Visit	-0.0350	(0.0621)
Coinsurance for Primary Care Physician Visit	-0.786	(0.612)
Dummy: Dental Coverage	0.233	(0.158)
Dummy: Hearing Exam	-0.386	(0.299)
Dummy: Hearing Aid	0.345**	(0.146)
Dummy: Routine Eye Exam	-0.0525	(0.134)
Insurer-Year FE?	Yes	
Market FE?	Yes	
Observations	3,955	
*** p<0.01, ** p<0.05, * p<0.1		

Note 1: The variable "Copay for 10 Inpatient Days" refers to the amount of copayments when a patient stays 10 days at an inpatient facility. Other variables with similar formats can be interpreted in a similar way.

Note 2: In addition to the variables included in the table, we also included variable dummy variables for insurers with missing information in each benefit. For example, some insurers have a coinsurance for a specialist visit instead of a copayment. In this case, we included a dummy variable that equals to one if information about copayment does not exist.

Table 21: Estimates for Parameters of Preference Heterogeneity

Variables	Estimates	Std. Error
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}=j]\times h_{it}$	0.879*	(0.485)
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]\times\mathbf{1}[h_{it}=0]$	1.449***	(0.467)
$\log\left(1+ad_{jmt}\right)\times\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]\times\mathbf{1}[h_{it}=1]$	0.470	(0.612)
Premium$\times h_{it}$	3.2e-4	(0.003)
$\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]$	-3.786***	(0.242)
$\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]\times h_{it}$	0.016	(0.127)
$\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]\times$Number of Firms in Market	0.008	(0.084)
$\mathbf{1}[d_{i,t-1}\neq j,d_{i,t-1}\geq 0]\times$Number of Firms in Market Squared	-0.007	(0.008)
$h_{it}\times MA$	0.181	(0.215)
$Income\times MA$	0.631***	(0.234)
$Income^2\times MA$	-0.131***	(0.035)
$\frac{Age}{65}\times MA$	-17.76**	(8.271)
$\left(\frac{Age}{65}\right)^2\times MA$	6.698*	(3.467)
Drug Coverage$\times h_{it}$	0.0147	(0.215)
Private Fee-for-Service Plan$\times h_{it}$	-0.832	(0.540)
Traditional Medicare Last Year$\times MA$	-0.338	(0.195)
MA Last Year$\times MA$	-0.463***	(0.180)
New to Medicare$\times MA$	-1.709***	(0.196)

Table 22: Counterfactual: Changes in Consumer Surplus from Baseline

Markets with Small Adv		Markets with Large Adv		Markets with Any Ad	
Partial Eq	Full Eq	Partial Eq	Full Eq	Partial Eq	Full Eq
Panel 1: Consumers That Are New to Medicare: Pr(Switching to MA)					
-2.6185	-7.6899	-21.838	-27.796	-14.299	-19.909
Panel 2: Consumers That Chose Traditional Medicare Last Year: Pr(Switching to MA)					
-.20552	-.59647	-1.534	-2.3085	-.95681	-1.5647
Panel 3: Consumers That Chose a MA Plan Last Year: Pr(Switching to different MA)					
-5.2011	-28.877	-44.763	-108.75	-32.149	-83.283

Note: Measured in terms of dollars. Annual Surplus.