Online Appendix

Advertising and Risk Selection in Health Insurance Markets

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A. Construction of Risk Score and Capitation Payment

The capitation payment to a Medicare Advantage (MA) plan for covering an individual between 2001 and 2005 is determined as the product of the benchmark rate and risk score. The benchmark rate is determined for each county-year, reflecting the county's past Medicare reimbursement costs. The benchmark rate for different counties in different years can be obtained from MA Ratebooks.[1]

Although the same benchmark rate is applied for all individuals within a county-year pair, a risk score depends on an individual's demographic characteristics and the previous year's claims, which makes the eventual capitation payment individual-specific. Until 2000, the risk score was initially determined from the demographic model, which is based on an individual's gender, age, disability, Medicaid enrollment, and institutional status. The demographic model uses the data from traditional Medicare (TM) and predicts the TM cost based on those characteristics. Based on the predictability of health care cost by those conditions, the weight on each demographic variable is made and these aggregate to the risk score. During the 2000–2003 period, the CMS made 10 percent of a risk score dependent on inpatient claims data using the PIP-DCG risk adjustment model, while 90 percent of the risk score was still determined by the demographic model. The weights in the demographic model are publicly available, and the SAS program that calculates a risk score based on the PIP-DCG model is publicly available as well.[2] With this information, we can calculate the risk score for an individual in the Medicare Current Beneficiary Survey (MCBS), which has claims history from the previous year.

Starting in 2004, the CMS began to use a more sophisticated risk adjustment system, where a risk score is determined by the hierarchical condition categories (HCC) model. Instead of just using crude demographic characteristics and inpatient claims, the HCC model also uses wide measures of disease conditions included in TM claims. The CMS gradually increased the weight for the HCC model in calculating a final risk score until 2007. In 2004, the HCC model was given the weight of 30 percent, while the demographic model was given the weight of 70 percent. In 2005,

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[1] See http://www.cms.gov/ MedicareAdvtgSpecRateStats/RSD/list.asp.

[2] The weblink for PIP-DCG model is https://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/ Ratebooks-and-Supporting-Data-Items/2003Rates.html?DLPage=2&DLEntries=10&DLSort=0&DLSortDir=descending.

2006, and 2007, the HCC model was given the weights of 50 percent, 70 percent, and 100 percent, respectively, while the demographic model was given the remaining weights. The program that calculates the risk score based on the HCC model is also publicly available.[3] The program allows us to calculate a risk score for individuals that have TM claims information from the previous year is available.

One issue in calculating a risk score is that we do not have access to claims information for incumbent Medicare beneficiaries who enrolled in MA in the previous year. As a result, risk scores can be calculated only for individuals who enrolled in TM in the previous year. As discussed in Section II, we do not need to impute risk scores for relatively new Medicare beneficiaries who spent less than the full 12 months in the Medicare system in the previous year because their risk scores are determined only by demographic information. We impute risk scores with the PIP-DCG and HCC models for incumbent beneficiaries who enrolled in MA in the previous year using the estimated relationship between risk scores and detailed health and demographic information for those who enrolled in TM in the previous year. Because the MCBS provides such information for all individuals, we can use this information to impute risk scores for those who enrolled in MA in the previous year.

For the imputation, we run regressions of the risk scores of TM enrollees on 85 variables describing their detailed health and demographic information. Specifically, we run separate regressions for individuals depending on whether an individual lived in a nursing home at the time of the survey because different health information is available depending on nursing home status.[4] Eventually, we run four regressions for the imputation: two regressions for the risk score with the HCC model and two regressions for the risk score with the PIP-DCG model. Many variables included in the regression describe a history of illness and are also used as inputs for the calculation of the risk score. Examples of the variables include whether one has diabetes, whether one has ever had cancer in a specific part of the body, and whether one has ever had heart disease. With the regression estimates, we calculate the PIP-DCG and HCC risk scores for individuals who enrolled in MA in the previous year. Although this imputation might result in numbers that are different from the actual risk scores for MA enrollees, we provide suggestive evidence in Section II.B that the imputation results in reasonable risk scores.

With this imputation procedure, we have all MCBS individuals' risk scores with the PIP-DCG and HCC models. Then we calculate the final risk score for each individual by blending the risk scores from the demographic, PIP-DCG, and HCC models using the appropriate weights for a given year. Finally, we calculate each individual's capitation payment by multiplying the bench-

[3]The weblink for the HCC model is https://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk-Adjustors-Items/Risk2006-2011.html?DLPage=2&DLEntries=10&DLSort=0&DLSortDir=descending.

[4]Individuals living in a nursing home are those who live in a "facility" in the MCBS.

mark rates with the final risk score.

B. Calculating Predicted TM Reimbursement Cost

By definition, an individual's reimbursement cost for TM is only observed for those who enrolled in TM. Thus, we impute the predicted TM reimbursement cost for MA enrollees. First, using TM enrollees in the MCBS, we regress an observed claims cost on variables that are created as a function of three measures of health status included in the demand model as well as the county-level average TM cost. Second, we calculate predicted costs for the TM enrollees using the estimated coefficients reported in Table A2. Finally, we calculate predicted costs for MA enrollees using the regression coefficient in the first step.

A caveat to the imputation of predicted TM costs for MA enrollees is that the regression might be potentially subject to selection bias because realized TM costs are observed conditional on the choice of TM. Because we control for many health measures including the HCC score, which is based on past insurance claims, we believe that there is likely to be a limited role for unobserved heterogeneity that affects both health care costs and the choice of TM over MA. Moreover, even if selection into MA based on unobserved characteristics exists, we expect that our results in Section III will be not qualitatively affected by the selection. Specifically, because observably healthy individuals select into MA plans, it is natural to expect that unobservably healthy individuals also select into MA plans as well. In this case, we overestimate the predicted cost of MA enrollees. We, therefore, need to adjust that the health care cost of MA enrollees is lower than the health care cost of TM enrollees with the same observed characteristics. In Section III, we show regression results where we discount the predicted costs of MA enrollees by introducing $w \in [0,1]$. We show that the main results are robust in Table 4 with respect to w. Moreover, our estimation of demand-side parameters does not depend on predicted TM costs but on direct health measures such as Phy/Cog, V/H, and HCC score. Thus, our main finding that advertising attracts healthy individuals does not depend on predicted TM costs. Thus, we believe that the omission of the selections will not have much of an impact for our main conclusion.

C. Direct Mail Advertising

This section provides a supplemental analysis using data on direct mail advertising. Although we find evidence that mass advertising is targeted to DMAs with higher potential profits from risk selection, insurers may further implement sophisticated targeting within a DMA. To pursue this possibility, we investigate the second measure of advertising: direct mail advertising. We believe that direct mailings are a very useful tool from an insurer's perspective for targeting its advertising toward 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.

The data set is from Mintel Comperemedia (Mintel henceforth), which is a database that tracks direct mail advertising in the United States. 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 about the 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 no MA insurer is available. Moreover, we selected households with at least one household head who is at least 64.[5]

1. Summary Statistics

Table A28 presents summary statistics from Mintel. In this data set, the unit of observation is an individual-month pair, meaning that an individual received 0.158 mailings per month from MA plans on average. Conditional on receiving at least one MA-related mailing, an individual received 1.24 mailings per month 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).[6] 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.

2. Evidence on Targeting and Its Impact on Demand

We study whether advertising is targeted and whether target advertising increases demand. We first investigate whether the targeting of direct mailings responded to the introduction of the comprehensive risk adjustment in 2004. Our hypothesis is that as it is more profitable to attract unhealthy individuals (in terms of risk score), insurers may want to attract relatively unhealthy individuals

[5] 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.

[6] 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).

starting in 2004. 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 positively correlated, as shown in Table A29.

A caveat to the hypothesis is that the risk adjustment policies may give insurers incentive to implement more sophisticated risk selection. For example, Brown et al. (2014) argue that enrolling Hispanics with higher risk scores will be much more profitable after the risk adjustment policy because Hispanics tend not to utilize health care compared with other races with the same health conditions and because a higher risk score will lead to a greater capitation payment after the risk adjustment policy. At least in the context of this example, however, insurers would like to target low-income individuals because Hispanics tend to have lower incomes in our data sample. Of course, the sophisticated targeting can be implemented in different ways. However, we believe that insurers may have access to information only related to income and demographics of each household. Thus, it is in general hard for them to know where to find individuals with specific health statuses, unless they were already a member of that insurance company's plan.

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:

$$\text{(A1)} \qquad y_{it} = \alpha_0 + \sum_{k=1}^{4} \alpha_{1,k} \mathbf{1}[I_{it} = k] + \sum_{k=1}^{4} \alpha_{2,k} \mathbf{1}[t \geq Oct\, 2003] \mathbf{1}[I_{it} = k] + \mathbf{X_{it}} \boldsymbol{\beta} + f_t + f_c + f_{mt} + \varepsilon_{it},$$

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 equation (A1), 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, $\mathbf{X_{it}}$ 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, number of Medicare beneficiaries in each county-year, and median household income for each county-year. Next, f_t represents the fixed effects for month-year t. In addition, f_c represents the county fixed effect for a combination of households. Finally, f_{mt} represents the fixed effect for each DMA-year pair (mt).

In equation (A1), 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 county fixed effect 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. Moreover, the DMA$\times$year fixed effect absorbs any variation in annual mass advertising, which varies at the DMA-year level. Thus, our specification controls for potential coordination between direct-mail and mass advertising at least at the annual level.

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:

$$y_{it} = \alpha_0 + \alpha_{1,zip} I_{zip(i),t} + \alpha_{2,zip} \mathbf{1}[t \geq Oct, 2003] I_{zip(i),t} + \mathbf{X_{it}} \boldsymbol{\beta} + f_t + f_c + f_{mt} + \varepsilon_{it} \tag{A2}$$

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 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 A30, 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 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 lower-income neighborhoods under the new regime. Because the unit of a zip-code-level income is $1,000, the estimate with the specification with a zip-code income suggests that a one standard deviation increase in a zip-code-level income ($28,000) leads to a 0.018 decrease in the number of monthly mailings from MA insurers, which is about 10 percent of the unconditional mean of the number of monthly mailings. 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 in the previous year or (ii) more likely to switch to a different MA insurer if the individual chose an MA insurer in the previous year.[7]

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 (A1) and (A2). Specifications (3) and (4) in Table A30 present results from the two regressions. Note that none of the estimated coefficients for the interactions between incomes and the new risk adjustment regime are positive. 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.

The insignificant impact of direct mail advertising on demand may partly result from firms' difficulties in accessing the true impact of targeted advertising on demands. Findings in recent research on advertising, such as Blake et al. (2015), suggest that advertisers might not know the effectiveness of their sophisticated targeting strategy, which may lead to a suboptimal advertising strategy. Thus, although MA insurers targeted the lower-income group after the risk adjustment, it is still possible that demand responses to targeted advertising are small.

It is still possible, however, that we have this result on direct mail advertising because the data for health insurance choices and the data for direct mail are obtained from different sources. With this data situation, it is difficult to accurately estimate the effect of direct mailing on the demand for MA. Therefore, we only view this evidence as suggestive.

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

D. Robustness of Estimates of the Common Effect of Advertising

1. Instrumental Variable Strategy

As a robustness check, we first implement an IV approach to estimate the common effect of advertisingα_0. As IVs, we use the Hausman-Nevo IV (Hausman, 1996, Nevo, 2001) and the profitability of risk selection constructed in Section III. We construct the Hausman-Nevo IV as the average advertising expenditures in DMAs located in the different states by the same parent company in the same year. As in the main specification, we include insurer$\times$county fixed effects and year fixed effects. The IV can be correlated with advertising in a market through several channels. First, it likely captures the common component in the cost of advertising for insurers under the same parent company. Second, it may also capture a risk selection channel. If the gain from risk selection is very different across markets, advertising in a market can be negatively correlated with advertising in other markets because advertising will be targeted to markets with greater profits from risk selection. If the gains are similar across markets, the correlation can be positive.

Because we include insurer$\times$county fixed effects, the main identification assumption is that changes in the IV over time is uncorrelated with $\Delta\xi_{jct}$. The IV may change over time because of supply-side factors such as a change in a common component in an insurer's cost of advertising or a change in the profitability of risk selection driven by risk adjustment policies. One caveat is that there may still be time-varying unobserved qualities that are correlated across markets, which may be also correlated with changes in the IV over time. By excluding advertising in DMAs in the same state in constructing the IV, we can at least address a concern about a possible correlation between unobserved qualities within a state.

Moreover, we also experiment with adding the profitability of risk selection as an additional IV ($rsprof^1_{mt}$ in equation (4)), which reflects the effects of the risk adjustment on incentives for risk selection. Because the variable may be correlated with average profitability, we also experiment with removing variation in $rsprof^1_{mt}$ that is correlated with the average profitability measure ($avprof_{mt}$ in equation (3)).[8] The identifying assumption is that an insurer's unobserved quality does not respond to changes in the profitability from risk selection. Thus, the validity of the identification assumption depends on how much we control for insurer's other potential risk selection tools that are time varying. Although it is not perfect, we believe that our approach to include an extensive list of plan characteristics in the demand model addresses this issue to some extent.

We report the IV first stage estimates in Table A9 in the Online Appendix and our estimates of the common effect of advertising (α_0) based on the IV strategy in Table A8. We find that the first

[8] Specifically, we regress $rsprof^1_{mt}$ on $avprof_{mt}$ and then use the residual from the regression as an IV.

stage regression is jointly significant. Moreover, we find that our estimates of α_0 are very similar across various specifications.

2. The Border Identification Strategy

As an additional robustness check for estimating the common effect of advertising, we also employ a border identification strategy. Our border identification strategy utilizes a discontinuity of advertising expenditures by the same insurer across a border between DMAs by comparing mean utilities for the same insurer in contiguous counties located on opposite sides of a DMA border. This identification strategy follows the recent marketing literature (Shapiro, 2016; Tuchman, 2016; Moshary, 2017), and the main idea behind this type of border approach is already seen in a seminal work by Holmes (1998). A DMA typically contains a major city and surrounding counties. Thus, there are "border counties" in an outer part of a DMA that are located right next to at least one county in a different DMA. In contrast, "non-border counties" are surrounded only by counties belonging to the same DMA. With this identification strategy, we compare mean utilities of the same insurer only in border counties on the opposite sides of a DMA border. The unobserved quality of plans offered by the same insurer is likely to be similar, but consumers might be exposed to different amounts of advertising by the same insurer because they happen to live in different DMAs.

For insurers in border counties, we specify ξ_{jct} in equation (7) in the following way:

$$\xi_{jct} = \xi_{jb(c)t} + \xi_{jc} + \Delta\xi_{jct}, \tag{A3}$$

where $b(c)$ refers to a DMA border to which county c belongs. For example, if a border between DMA m_1 and DMA m_2 is called b_{12}, then $b(c) = b_{12}$ for any border counties c belonging to either m_1 or m_2. The first term $\xi_{jb(c)t}$ refers to an insurer×border×year fixed effect that would capture insurer j's unobserved characteristics in year t that are common to insurer j's plans in all counties that share border $b(c)$. The second term ξ_{jc} is an insurer×county fixed effect that captures systemic time-invariant differences in demand for insurer j in different counties within $b(c)$. Lastly, $\Delta\xi_{jct}$ is the remaining unobserved characteristic, which is assumed to be uncorrelated with $\ln\left(1+ad_{jm(c)t}\right)$. With this specification of ξ_{jct}, the identifying assumption is similar to that in a difference-in-difference regression. The identifying assumption is that unobserved differential trends of mean utilities for the same insurer $(\Delta\xi_{jct})$ are uncorrelated with trends of advertising spending by the insurer in different DMAs along border b.

The validity of the identifying assumption hinges on how much these fixed effects control for time-varying unobserved characteristics. Although it is difficult to directly verify a violation of the identifying assumption, we can still verify whether an insurer's plans on the opposite sides of a border are systemically different from each other with respect to their observed characteristics. If plans from the same insurer are very different across a border, then it is likely that their unobserved characteristics are very different as well. In Table A25, we compare characteristics of plans and county characteristics in border counties on the opposite sides of a border between DMAs. The table is created in the following way. For each insurer-border-year, all plans in the DMA where the insurer spends less on advertising are put under Group 1, and all plans in the other DMA where the insurer spends more on advertising are put in Group 2. Of course, advertising spending is different between the first and second columns by construction. The T-test shows that most characteristics on either side of a border are not statistically different. However, counties with more advertising tend to have average TM costs and average TM costs net of capitation benchmark.

One thing to note from Table A25 is that there is little variation of premiums across DMA borders. However, it does not imply that advertising has little impacts on an insurer's pricing. An insurer's pricing would typically depend on the expected costs of providing insurance, which are affected by (a) the insurer's risk pool, which may be affected by advertising; and (b) other determinants of health care cost (e.g., regional health care costs). As reported in Table A25, we find that, health care costs, measured in terms of county-level average TM costs, tend to be higher in counties in DMAs with higher advertising spending compared with neighboring counties in other DMAs with lower advertising spending. County benchmarks of capitation payments in these counties do not completely compensate for higher costs. We find that this cost difference is not explained by regional differences in the distribution of health statuses because Table A26 shows that realized TM reimbursement costs are greater for border counties with more advertising conditional on health status. Thus, the variation in average TM costs across DMA borders reflects regional differences in health care costs at least in this context. Advertising and health care costs will have opposite impacts on premiums: (a) higher advertising spending will lead to better risk pools and lower premiums; and (b) higher health care costs will lead to higher premiums. Thus, the fact that premiums are similar across DMA borders does not imply that advertising has no impact on premiums.[9,10]

[9]In Section VII, we estimate our supply-side model while accounting for this cross-sectional heterogeneity as well as other patterns of advertising and premiums, including a negative correlation between advertising and premiums among entire markets shown in Table 1 and their time series variations in the data, based on several ingredients, such as the insurer's risk pool, market competition, and regional health care costs. Given the estimates that rationalize all the premium variations, we conduct the counterfactual analysis that shuts down advertising while holding the insurer-market specific cost parameter *constant*.

[10]Table A25 shows that the net monthly TM cost is $14 greater in border counties with more advertising than in border counties with less advertising. The table also shows that the average premium is $36 per month, which implies that the difference in net TM cost is as large as 39 percent of the average premium. Thus, if we attribute the little observed variation of premiums across the border to risk selection induced by advertising that offsets the difference in net TM costs across the border, then the risk selection induced by advertising accounts for a very significant variation in premiums. Quantitatively, such a finding is consistent with our finding in Section VII.B.

Finally, we would like to mention limitations with the border strategy. First, identification is only coming from local variation in advertising and market shares – that is, we do not use variation in non-border counties. Thus, one needs to use caution when extrapolating the coefficient estimates to non-border counties. Table A27 shows that market characteristics in border and non-border counties are different to some degree, such as the number of insurers, MA penetration rates, and county benchmark. Second, it is still possible that consumers living in border counties may be exposed to very similar amounts of advertising because they may make a trip to the opposite side of the border. This may weaken the sharp discontinuity of advertising expenditures across a DMA border. Lastly, if regional health care costs affects unobserved characteristics, then the border approach will lead to a biased estimate because regional health costs are different across the border as we discussed above.

Our estimation result is reported in Table A8. We find that the border strategy results in an estimate that is very similar to estimates from other approaches.

E. Diagnosis to Knittel and Metaxoglou (2014) Critique

Knittel and Metaxoglou (2014) find that parameter estimates may converge to a local minimum or saddle points in random-coefficients demand systems. To make sure that our estimates are not stuck at such points, we did the following. First, for the contraction mapping process, we used a strict tolerance criterion of $1e^{-14}$, which is much stricter than the level used in some papers estimating random-coefficient demand models. For example, Berry et al. (1995) use a tolerance of $1e^{-4}$. Second, we experimented with different starting values for the nonlinear optimization and find that convergence occurs at a similar value. Third, we also experimented with a derivative-free optimization algorithm and find that convergence occurs at a similar value to our baseline estimates, for which we used an algorithm that uses derivatives.

F. Details on the Supply Side

1. Characterization of Optimal Pricing and Estimation

For the optimal pricing for plans of insurer j in market ct, the first-order conditions for the optimal premiums for the plans given by equation (10) can be rewritten in a matrix form as follows:

$$\text{(A4)} \qquad \mathbf{Q_{jct}} + \mathbf{dCAP_{jct}} + \mathbf{dQ_{jct}}\big(\mathbf{P_{jct}} - \mathbf{X_{jct}}\boldsymbol{\omega}_x - \mathbf{H_{jct}}\big) = \mathbf{dFFS_{jct}}(\mathbf{1}\omega_{FFS} + \mathbf{X_{jct}}\boldsymbol{\omega}_{x,FFS}),$$

where

$$\mathbf{Q_{jct}} = \begin{bmatrix} Q_{j1ct} \\ \vdots \\ Q_{jL(j)ct} \end{bmatrix}, \mathbf{P_{jct}} = \begin{bmatrix} P_{j1ct} \\ \vdots \\ P_{jL(j)ct} \end{bmatrix}, \mathbf{1} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}, \mathbf{dQ_{jct}} = \begin{bmatrix} \frac{\partial Q_{j1ct}}{\partial p_{j1ct}} & \cdots & \frac{\partial Q_{jL(j)ct}}{\partial p_{j1ct}} \\ \vdots & \ddots & \vdots \\ \frac{\partial Q_{j1ct}}{\partial p_{jL(j)ct}} & \cdots & \frac{\partial Q_{jL(j)ct}}{\partial p_{jL(j)ct}} \end{bmatrix},$$

$$\mathbf{dCAP_{jct}} = \begin{bmatrix} \frac{\partial CAP_{j1ct}}{\partial p_{j1ct}} & \cdots & \frac{\partial CAP_{jL(j)ct}}{\partial p_{j1ct}} \\ \vdots & \ddots & \vdots \\ \frac{\partial CAP_{j1ct}}{\partial p_{jL(j)ct}} & \cdots & \frac{\partial CAP_{jL(j)ct}}{\partial p_{jL(j)ct}} \end{bmatrix} \times \mathbf{1}, \text{ where } \frac{\partial CAP_{jlct}}{\partial p_{jl'ct}} \equiv \int_{\mathbf{z_{it}}} CAP_t(\mathbf{z_{it}}) \frac{\partial q_{jlct}(\mathbf{z_{it}})}{\partial p_{jl'ct}} dF_{ct}(\mathbf{z_{it}}),$$

$$\mathbf{dFFS_{jct}} = \begin{bmatrix} \frac{\partial FFS_{j1ct}}{\partial p_{j1ct}} & \cdots & \frac{\partial FFS_{jL(j)ct}}{\partial p_{j1ct}} \\ \vdots & \ddots & \vdots \\ \frac{\partial FFS_{j1ct}}{\partial p_{jL(j)ct}} & \cdots & \frac{\partial FFS_{jL(j)ct}}{\partial p_{jL(j)ct}} \end{bmatrix}, \text{ where } \frac{\partial FFS_{jlct}}{\partial p_{jl'ct}} \equiv \int_{\mathbf{z_{it}}} FFS_{ct}(\mathbf{h_{it}}) \frac{\partial q_{jlct}(\mathbf{z_{it}})}{\partial p_{jl'ct}} dF_{ct}(\mathbf{z_{it}}),$$

$$\mathbf{X_{jct}} = \begin{bmatrix} \mathbf{x'_{j1ct}} \\ \vdots \\ \mathbf{x'_{jL(j)ct}} \end{bmatrix}, \mathbf{H_{jct}} = \begin{bmatrix} \eta_{j1ct} \\ \vdots \\ \eta_{jL(j)ct} \end{bmatrix}.$$

Equation (A4) can rewritten by dividing both sides by $\mathbf{dQ_{jct}}$:

$$\text{(A5)} \quad \mathbf{dQ_{jct}^{-1}}\left(\mathbf{Q_{jct}} + \mathbf{dCAP_{jct}}\right) + \mathbf{P_{jct}} = \mathbf{X_{jct}}\boldsymbol{\omega}_x + \mathbf{dQ_{jct}^{-1}dFFS_{jct}}(\mathbf{1}\omega_{FFS} + \mathbf{X_{jct}}\boldsymbol{\omega}_{x,FFS}) + \mathbf{H_{jct}}$$

Note that the left-hand side of equation (A5) can be calculated using the estimated demand model. The right-hand-side variables can also be calculated up to parameter $\boldsymbol{\omega}$ and error term $\mathbf{H_{jct}}$. Therefore, parameter $\boldsymbol{\omega}$ can be estimated using equation (A5).

One challenge in estimating $\boldsymbol{\omega}$ is that elements of $\mathbf{dQ_{jct}^{-1}dFFS_{jct}}$ are endogenous to elements of $\mathbf{H_{jct}}$. Each element of matrix $\mathbf{dQ_{jct}^{-1}dFFS_{jct}}$ measures the expected health care cost of a marginal consumer of each plan. Moreover, each element of $\mathbf{H_{jct}}$ is an insurer-plan-county-year-specific shock to the marginal cost defined in equation (11), η_{jlct}. The marginal cost shock η_{jlct} will affect insurer j's pricing and advertising decisions. As a result, η_{jlct} will affect the average health status of a marginal consumer to the extent that a premium and advertising expenditure have differential effects on the demand of consumers with different health statuses. In fact, we find that advertising has such effects, as reported in Section VI.

We solve the endogeneity problem with an instrumental variable. We use the average reimbursement cost in TM in county c and year t (TMC_{ct}) as an instrument. The main idea is that TMC_{ct} is correlated with the predicted TM reimbursement cost $FFS_{ct}(\mathbf{h_{it}})$, a component of $\mathbf{dQ_{jct}^{-1}dFFS_{jct}}$, because overall health care costs in county c in year t will affect both TMC_{ct} and $FFS_{ct}(\mathbf{h_{it}})$. The main identification assumption is that TMC_{ct} is not correlated with η_{jlct} for all j and l, conditional on all control variables in equation (A5). Because we include an extensive list of insurance product variables as well as the measurement of health care costs, the residual marginal cost is likely to capture insurer-specific administrative costs, which are less likely to correlate with TM reimbursement costs. Estimates of ω are reported in Table A20.

G. Discussion about Upcoding

One potential issue in dealing with risk scores for MA enrollees is MA insurers' upcoding of diagnoses, which artificially increases risk scores. In fact, Geruso and Layton (2015) find evidence that MA insurers upcode diagnostic codes to increase capitation payments for their enrollees. When we construct imputed HCC scores for those who enrolled in MA in the previous year, we do not adjust the imputed HCC scores for the possibility that their risk scores may be affected by an insurer's upcoding. Although we showed that our imputed HCC scores look reasonable, it is important to acknowledge how our analysis may be affected by not incorporating upcoding. Below, we discuss that, at least in our analysis, a potential bias in our results will be very limited and will not alter our main conclusion.

Preliminary Analysis of Targeted Advertising In our preliminary analysis in Section III, we construct a measure of the profitability of risk selection ($rsprof_{mt}$) using the individual-level capitation payment, which is a function of the HCC score. Thus, it is possible that the lack of incorporating potential upcoding might lead to measurement errors for $rsprof_{mt}$.

Note that upcoding will not always lead to measurement errors. Suppose that upcoding affects the HCC scores of healthy and unhealthy individuals by similar amounts. Then, there will not be any effects on $rsprof_{mt}$ because $rsprof_{mt}$ is the standard deviation of potential profits across individuals with different health statuses.

However, upcoding might increase the HCC scores of certain individuals more than other individuals. Because upcoding can occur when an enrollee visits a physician, upcoding is presumably more likely for unhealthy individuals who would see their physicians more frequently than healthy individuals. In this case, our measure of $rsprof_{mt}$ is likely greater than an actual $rsprof_{mt}$ from an MA insurer's perspective because upcoding will increase potential profits from unhealthy individuals more than those from healthy individuals. Even in this case, if the magnitude of the measure error for $rsprof_{mt}$ is uniform across DMAs in a given year, then the measurement error will not affect the estimate of the coefficient for $rsprof_{mt}$ – β_2 in equation (2) – because of the year fixed effect in the regression.

The estimate of β_2 will be biased if the measurement error for $rsprof_{mt}$ is larger for certain

DMAs in certain years than other DMA-year pairs. We will argue that the coefficient β_2 will be underestimated in a likely scenario. We expect that if magnitudes of the error are different across DMAs, then those with higher health care costs are more likely to have greater measurement errors. Because a capitation payment is a product of a benchmark rate and the HCC score, and because the benchmark rate is usually greater in a region with higher health care costs, even the identical increases in HCC scores induced by upcoding in different DMAs will result in a greater increase in a capitation payment in a DMA with a high cost. In this case, we expect that our measure of $rsprof_{mt}$ in the data will overstate the actual $rsprof_{mt}$ from the insurer's perspective to a greater degree in DMAs with higher costs than other DMAs. In other words, $rsprof_{mt}(data) - rsprof_{mt}(actual)$ is greater in the former DMAs than in the latter DMAs. This is because upcoding will likely increase profits from unhealthy individuals more than profits from healthy individuals, which will reduce the dispersion of profits from different health statuses. Moreover, these measurement errors are likely to be greater in the years after the comprehensive risk adjustment because upcoding is possible when risk scores are calculated based on diagnostic codes. Here, recall that differential changes in $rsprof_{mt}$ across DMAs over time are the identifying variation for the coefficient β_2. As shown in Table A4, the risk adjustment decreased our measures of $rsprof_{mt}$ to a larger degree in DMAs with high health care costs compared with other DMAs. If our measures of $rsprof_{mt}$ in the data overstate the actual $rsprof_{mt}$ more in the former DMAs after the risk adjustment, then the risk adjustment will decrease $rsprof_{mt}$ even more in the former DMAs from the insurer's perspective than those in the latter DMAs. In other words, the data variation in $rsprof_{mt}$ will be smaller than the actual variation in $rsprof_{mt}$ from the insurer's perspective, which will lead to underestimation of the coefficient β_2.

Counterfactual Analysis An insurer's profit function in equation (8) depends on capitation payments from those who enrolled in MA in the previous year, for whom insurers will be able to engage in upcoding. Upcoding will potentially increase an insurer's profit from these individuals, but we do not explicitly incorporate the possibility in our framework. However, we believe that our main conclusion from the counterfactual analysis is not likely to change. Note that those who enrolled in MA in the previous year are not likely to respond very much to a change in pricing or advertising because of the switching cost. An insurer's optimal pricing and advertising depend on the behaviors of marginal consumers, who are likely to consist of new-to-Medicare individuals that do not face the switching cost. Moreover, insurers cannot upcode these individuals' risk scores because they only depend on demographic factors. Thus, the effect of upcoding on the revenue from the marginal consumer will be limited, which in turn implies that upcoding would have only limited impacts on our counterfactual results.

H. Details about the Counterfactual Experiments with Better Risk Adjustment Systems

Here, we provide details about the counterfactual experiments with better risk adjustment systems in Section VII.C. As mentioned in that section, we conduct this counterfactual to qualitatively illustrate the impacts of alternative risk adjustment systems on an insurer's behavior. For this counterfactual, we specify the functional form of the cost function of advertising as

$$AdCost_{jmt}(ad_{jmt}) = FC_{jmt}\mathbf{1}\left[ad_{jmt} > 0\right] + \zeta_{jmt}ad_{jmt}, \tag{A6}$$

where FC_{jmt} is the fixed cost of advertising, which is included to rationalize the significant fraction of insurers without advertising, and ζ_{jmt} is the parameter that captures a potential heterogeneous marginal cost of advertising across insurers.

We use Nash equilibrium conditions for the optimal pricing and advertising to estimate parameters in the supply-side model. The optimality conditions for the pricing remain the same as in equation (10). The necessary conditions for the optimal advertising level ad^*_{jmt} for each insurer are as follows:

$$\begin{aligned} \frac{\partial \Pi_{jmt}}{\partial ad_{jmt}} &= 0 \text{ for } ad^*_{jmt} > 0; \\ \Pi_{jmt}(\mathbf{p}^*_{jmt}, ad^*_{jmt}) &\geq \Pi_{jmt}(\mathbf{p}'_{jmt}, ad'_{jmt}) \text{ for any } \mathbf{p}'_{jmt}, \text{ any } ad^*_{jmt} \geq 0 \text{ and any } ad'_{jmt} \geq 0, \end{aligned} \tag{A7}$$

where $\mathbf{p}^*_{jmt}$ is a vector of equilibrium premiums for all of insurer j's plans in DMA m in year t, which satisfy the first-order condition in equation (10). Note that the fixed cost of advertising results in the inequality condition. In order to avoid the complication of dealing with the inequality condition, we consider a counterfactual experiment where only insurers with positive baseline advertising reoptimize advertising levels to other interior points, which are determined by equation (A7). The impact of this restriction should be negligible in our counterfactual that introduces a better risk adjustment system, which leads insurers to reduce advertising. Moreover, we only consider a marginal change in risk adjustment because a drastic change would make the role of the fixed cost of advertising more important. With this assumption, we only need to recover ζ_{jmt} using the first-order condition in equation (A7).

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I. Supplemental Tables

Table A1: Summary Statistics for Health Measures

	Phy/Cog=0		Phy/Cog=1		V/H=0		V/H=1		Overall	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HCC Score	0.91	(0.59)	1.38	(0.87)	1.01	(0.70)	1.29	(0.79)	1.06	(0.72)
Problem with Vision or Hearing	0.11	(0.31)	0.29	(0.46)					0.17	(0.37)
Problem with Cognition or ADL					0.27	(0.44)	0.55	(0.50)	0.31	(0.46)
Observations	21540		12344		27529		6355		33884	

Source: MCBS 2001–2005.

Table A2: Reimbursement Costs for TM Enrollees

Variables	Estimate	Standard Error
Average TM Cost at County level	-0.161	(0.199)
HCC Score	103.889	(98.375)
V/H=1	-102.898	(106.319)
Phy/Cog=1	-172.518	(81.722)
AverageTM Cost at County level × HCC Score	0.518	(0.209)
AverageTM Cost at County level × V/H=1	0.214	(0.230)
AverageTM Cost at County level × Phy/Cog=1	0.806	(0.170)
Observations	37,070	
R-squared	0.119	

Note: The sample for this analysis consists of individuals in the MCBS who stayed with TM. Standard errors are in parentheses.

Table A3: Diagnostics for the Risk Score Imputation: Relationship between Individual Health and Advertising

	TM or No Switcher		Switching to MA with Advertising = 0		Switching to MA with Advertising > 0	
	Mean	SD	Mean	SD	Mean	SD
HCC Score	1.07	(0.73)	0.86	(0.50)	0.85	(0.48)
Age	72.99	(11.28)	70.22	(9.13)	70.84	(8.97)
percent on Medicaid	0.15	(0.36)	0.11	(0.31)	0.09	(0.29)
percent Ever Had Stroke	0.11	(0.31)	0.08	(0.28)	0.09	(0.28)
percent Have Diabetes	0.19	(0.39)	0.20	(0.40)	0.19	(0.39)
percent Ever Had Heart Attack	0.13	(0.34)	0.07	(0.26)	0.09	(0.29)
Observations	32,835		538		511	

Source: MCBS 2001–2005; AdSpender 2001–2005.

Table A4: Geographical Targeting of Mass Advertising: Summary Statistics

	(1) DMAs with Low Profit from Risk Selection		(2) DMAs with High Profit from Risk Selection	
Variables	Before 2004	After 2003	Before 2004	After 2003
Advertising per Capita ($)	0.05	0.14	0.10	0.15
SD–Phy/Cog, V/H ($rsprof^1_{mt}$)	91.93	93.28	176.35	155.55
SD–HCC score ($rsprof^2_{mt}$)	98.25	42.46	153.16	79.16
Average Potential Profit ($avprof_{mt}$)	86.08	155.60	60.47	104.72
County Benchmark ($)	512.51	591.77	576.62	639.46
Average TM Cost ($)	447.90	490.34	573.93	624.91
Number of Insurers	2.76	3.78	4.46	6.30
Number of Medicare Beneficiaries in DMA	291443	326695	858302	985929
Observations	418	350	308	217

Source: MCBS 2001–2005; AdSpender 2001–2005; CMS SPC Files 2001–2005.
Note: Column (1) presents the summary statistics of DMAs with the profitability of risk selection defined by $rsprof^1_{mt}$ is below the mean before 2004. Column (2) presents the summary statistics of DMAs with the profitability of risk selection defined by $rsprof^1_{mt}$ is above the mean before 2004. The unit of observation is an insurer-DMA-year. Columns labeled "Before 2004" contain averages over insurer-DMA-year from 2001 to 2003. Columns labeled "After 2003" contain averages over insurer-DMA-year from 2004 to 2005.

Table A5: Geographical Targeting of Mass Advertising: Year-to-Year Variation for Main Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	$w = 1$		$w = 0.9$		$w = 0.8$	
Average Profit ($avprof_{mt}$)	0 .00026	0 .00015	0.00026	0.00027	0.00023	0.00028
	(0.00030)	(0.00036)	(0.00030)	(0.00035)	(0.00031)	(0.00031)
SD–Phy/Cog,V/H ($rsprof^1_{mt}$)	0.00167	0.00195	0.00188	0.00186	0.00209	0.00173
	(0.00056)	(0.00064)	(0.00061)	(0.00068)	(0.00068)	(0.00072)
SD–HCC score ($rsprof^2_{mt}$)		-0.00053		0.00005		0.00052
		(0.00079)		(0.00067)		(0.00054)
Number of Insurers	0.485	0.507	0.499	0.496	0.512	0.471
	(0.248)	(0.246)	(0.247)	(0.246)	(0.245)	(0.243)
Fraction of Healthy (Phy/Cog, V/H)	-0.0133	-0.0132	-0.0131	-0.0131	-0.0129	-0.0127
	(0.00765)	(0.00767)	(0 .00763)	(0.00771)	(0.00759)	(0.00743)
Number of Medicare Enrollees	2.51e-07	2.34e-07	2.52e-07	2.53e-07	2.49e-07	2.38e-07
	(2.05e-07)	(2.06e-07)	(2.06e-07)	(2.04e-07)	(2.07e-07)	(2.10e-07)
R-squared	0.553	0.553	0.553	0.553	0.553	0.553
Observation	1263	1263	1263	1263	1263	1263

Note: All specifications include Year FE, Insurer FE, and DMA FE. Standard errors are clustered at DMA level and calculated with 200 block bootstrapping simulations. Standard errors are in parentheses.

Table A6: Geographical Targeting of Mass Advertising: Differential Profits

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	$w = 1$		$w = 0.9$		$w = 0.8$	
Average Profit ($avprof_{mt}$)	0.00017	0.00014	0.00017	0.00012	0.00017	0.0000991
	(0.00055)	(0.00038)	(0.00058)	(0.00039)	(0.00061)	(0.00039)
Differential Profit–Phy/Cog,V/H ($rsprof^1_{mt}$)	0.00127	0.00108	0.00146	0.00122	0.00168	0.00136
	(0.00046)	(0.00034)	(0.00051)	(0.00037)	(0.00058)	(0.000409)
Differential Profit–HCC score ($rsprof^2_{mt}$)	-0.00046	-0.00039	-0.00055	-0.00044	-0.00066	-0.00049
	(0.00057)	(0.00039)	(0.00059)	(0.00041)	(0.00062)	(0.00042)
Number of Insurers	0.403	0.337	0.426	0.361	0.456	0.39
	(0.356)	(0.271)	(0.357)	(0.268)	(0.358)	(0.265)
Frac of Healthy (Phy/Cog, V/H)	-0.0128	-0.0131	-0.0125	-0.0128	-0.0121	-0.0124
	(0.00851)	(0.00781)	(0.00845)	(0.00781)	(0.00838)	(0.00779)
Number of Medicare Enrollees	2.16e-07	2.40e-07	2.23e-07	2.53e-07	2.34e-07	2.68e-07
	(2.39e-07)	(2.11e-07)	(2.38e-07)	(2.11e-07)	(2.37e-07)	(2.12e-07)
Specification	before/after	year-to-year	before/after	year-to-year	before/after	year-to-year
R-squared	0.555	0.554	0.555	0.554	0.555	0.554
Observation	1270	1258	1270	1258	1270	1258

Note: All specifications include Year FE, Insurer FE, and DMA FE. Columns (1), (3), and (5) present results with specifications, where $avprof_{mt}$, $rsprof^1_{mt}$, and $rsprof^2_{mt}$ are calculated by pooling together potential profits from individuals in years before the risk adjustment and pooling together the profits in years after the risk adjustment. Columns (2), (4), and (6) present results with specifications, where $avprof_{mt}$, $rsprof^1_{mt}$, and $rsprof^2_{mt}$ are calculated for each year. Standard errors are clustered at DMA level and calculated with 200 block bootstrapping simulations. Standard errors are in parentheses. Each column presents results with a specification where $cost(\mathbf{x})$ is defined to be $w\times$Predicted TM cost for individual characteristic $\mathbf{x}$.

Table A7: Within-Insurer Variation of Plan Characteristics

	Levels		Deviations
	Mean	SD	SD
Premium	0.357	(0.436)	(0.264)
Preventive Dental Coverage	0.220	(0.404)	(0.162)
Comprehensive Dental Coverage	0.068	(0.245)	(0.091)
Copay for Outpatient Clinic	0.086	(0.425)	(0.050)
Routine Hearing Exam	0.611	(0.480)	(0.194)
Hearing Aids	0.133	(0.338)	(0.088)
Copay for Prescription Drugs	0.408	(0.416)	(0.290)
Drug Coverage	0.668	(0.471)	(0.363)
Copay for Primary Care Physician	1.106	(0.764)	(0.445)
Copay for Specialist	0.176	(0.104)	(0.056)
Copay for Skilled Nursing Facility	0.233	(0.319)	(0.115)
Copay for Inpatient Care	0.142	(0.432)	(0.127)
Copay for Inpatient Stay	0.135	(0.234)	(0.124)
Gym Membership	0.253	(0.429)	(0.165)
Routine Eye Exam	0.833	(0.366)	(0.224)
Eyewear	0.691	(0.453)	(0.231)
Copay for Emergency Care	4.223	(1.078)	(0.523)
Observations	10228		10228

Source: MCBS 2001-2005; Medicare Compare Files 2001–2005.
Note: To create this table, we match each MA enrollee in the MCBS to all plans offered by the insurer that the MA enrollee chose and then calculate summary statistics of the plan characteristics. The first column, labeled "Levels," presents summary statistics of the plan characteristics. The second column, "Deviations," presents summary statistics of a plan-level deviation from the average value of each characteristic within each insurer chosen by each MA enrollee. Because we condition on ξ_{jct} in equation (5), variation in these deviations would identify the parameters for plan characteristics. Note that the mean of each characteristics under "Deviations" is equal to zero by construction.

Table A8: Estimates for Parameters in Mean Utility (δ_{jmt}) for the Benchmark Model

	(1)	(2)	(3)	(4)	(5)	(6)
	FE OLS1	FE OLS2 (main)	IV1	IV2	IV3	Border Strategy
Advertising Spending per Capita	0.148	0.0549	0.019	0.359	0.231	0.202
	(0.095)	(0.118)	(0.352)	(0.339)	(0.341)	(0.322)
HMO	0.702	0.678	0.676	0.689	0.684	-
	(0.207)	(0.207)	(0.208)	(0.207)	(0.208)	-
FE1	Firm	Firm×County	Firm×County	Firm×County	Firm×County	Firm×County
FE2	County	-	-	-	-	Firm×Border ×Year
IV1	-	-	Hausman-Nevo	Hausman-Nevo	Hausman-Nevo	-
IV2	-	-	-	Profit from Risk Selection 1	Profit from Risk Selection 2	-
N.Obs	8114	8114	8114	8114	8114	2977
R-squared	0.602	0.666	0.666	0.666	0.666	0.861

Note: Column (1) presents estimates with the specification, where we deal with the endogeneity of advertising with firm and county fixed effects. Column (2) presents estimates with the main specification, where we deal the endogeneity of advertising with firm-county fixed effects. Column (3) presents the IV regression with the Hausman-Nevo IV only. Column (4) presents the IV regression with the Hausman-Nevo IV as well as the profitability from risk selection as an IV ($rsprof^1_{mt}$ in equation (4)). Column (5) presents the IV regression with the Hausman-Nevo IV as well as $rsprof^1_{mt}$ without variation correlated with the average profitability ($avprof_{mt}$ in equation (3)). Column (6) presents the border identification strategy. In addition, all specifications include the following set of variables as control variables: year fixed effects, dummy variables for the number of plans offered by an insurer in the model; dummy variables for the number of plans offered by an insurer in the original data. Note that last two variables are not identical because we aggregate original plans up to construct four different types of plans offered by an insurer in the model, as explained in Section II. The first stage regression for the instruments in Columns (3), (4), and (5) are reported in Table A9.

Table A9: First Stage Regression for the IV Estimation of Mean Utility (δ_{jmt}) for the Benchmark Model

	(1)	(2)	(3)
	IV1	IV2	IV3
Hausman-Nevo for 2005	0.643	0.659	0.654
	(0.046)	(0.047)	(0.047)
Hausman-Nevo for 2004	0.159	0.169	0.166
	(0.028)	(0.029)	(0.029)
Hausman-Nevo for 2003	-0.119	-0.104	-0.104
	(0.045)	(0.045)	(0.045)
Hausman-Nevo for 2002	-0.0458	-0.0406	-0.0392
	(0.0674)	(0.0668)	(0.0675)
Hausman-Nevo for 2001	-0.499	-0.481	-0.482
	(0.155)	(0.155)	(0.155)
Profit from Risk Selection 1		0.000455	
		(0.000109)	
Profit from Risk Selection 2			0.000365
			(0.000115)
F-Statistics	68.2	55.6	55.3
FE	Firm-County	Firm-County	Firm-County
N.Obs	8114	8114	8114
R-squared	0.671	0.674	0.672

Note: For an insurer in year t, Hausman-Nevo for year t is equal to the insurer's parent company's average advertising in DMAs outside the insurer's own state in year t. For an insurer in an year other than t, the variable is equal to zero. Thus, the coefficients for Hausman-Nevo IV are year specific. This specification follows Nevo (2001) and allows for a flexible correlation between the IV and the main endogenous variable (i.e. advertising). Columns (1) to (3) present the first-stage results for the regression specifications in columns (3) to (5) in Table A8. In the first-stage regressions, we also include the same set of control variables as in specifications in columns (3) to (5) in Table A8.

Table A10: Estimates for Parameters for Common Effects for the Benchmark Model

	Estimates	Standard Error
Premium	-0.988	(0.156)
Preventive Dental Coverage	-0.488	(0.163)
Comprehensive Dental Coverage	0.808	(0.303)
Copay for Outpatient Clinic	0.372	(0.306)
Missing Value for Copay for Outpatient Clinic	-0.050	(0.495)
Routine Hearing Exam	-0.706	(0.166)
Hearing Aids	-0.270	(0.274)
Copay for Prescription Drugs	-0.388	(0.147)
Drug Coverage	0.740	(0.437)
Copay for Primary Care Physician	-0.341	(0.108)
Missing Value for Primary Care Physician	-0.094	(0.231)
Copay for Specialist	-1.479	(0.967)
Missing Value for Copay for Specialist	-0.135	(0.342)
Copay for Skilled Nursing Facility	0.003	(0.265)
Copay for Inpatient Care	0.126	(0.153)
Copay for Inpatient Stay	0.095	(0.291)
Gym Membership	-0.011	(0.169)
Routine Eye Exam	0.258	(0.202)
Eyewear	0.089	(0.161)
Copay for Emergency Care	0.113	(0.100)
Missing Value for Copay for Emergency Care	-0.240	(0.480)
Missing Value for Copay for Prescription Drugs	-0.964	(0.444)
Missing Value for Copay for Skilled Nursing Facility	-0.158	(0.217)
Missing Value for Copay for Inpatient Care	-0.125	(0.175)

Note: Standard errors are in parentheses.

Table A11: Estimates for Parameters of Preference Heterogeneity for the Benchmark Model

Variable	Estimates	Standard Error
Switch x J	0.443	(0.510)
Switch x J-squared	-1.018	(0.387)
MA x Phy/Cog	-0.126	(0.138)
MA x V/H	0.292	(0.158)
MA x HCC Score	-0.133	(0.115)
MA x MA Last Year x Year 2001	0.758	(0.222)
MA x MA Last Year x Year 2002	0.787	(0.232)
MA x MA Last Year x Year 2003	0.687	(0.248)
MA x MA Last Year x Year 2004	0.499	(0.244)
MA x MA Last Year x Year 2005	0.747	(0.257)
MA x New Medicare Beneficiary x Year 2001	-0.351	(0.219)
MA x New Medicare Beneficiary x Year 2002	-0.483	(0.228)
MA x New Medicare Beneficiary x Year 2003	-1.187	(0.224)
MA x New Medicare Beneficiary x Year 2004	-1.232	(0.204)
MA x New Medicare Beneficiary x Year 2005	-1.102	(0.223)

Note: Standard errors are in parentheses.

Table A12: Estimates for Parameters of Preference Heterogeneity for the Model with the Full Interaction

		Phy/Cog	V/H	HCC Score	Switch Dummy	Common Effects
Advertising	New Medicare	-1.034	-1.439	-0.009	0.875	-0.052
	/Switch	(0.302)	(0.554)	(0.269)	(0.439)	
	Non-Switch	0.289	-0.725	0.045		(0.125)
		(0.401)	(0.509)	(0.352)		
Premium	New Medicare	-0.217	-0.264	-0.037	0.152	-1.023
	/Switch	(0.227)	(0.268)	(0.195)	(0.231)	
	Non-Switch	-0.082	0.066	0.193		(0.159)
		(0.162)	(0.182)	(0.149)		
Drug Coverage	New Medicare	0.064	-0.254	-0.212	-0.199	0.725
	/Switch	(0.220)	(0.259)	(0.184)	(0.220)	
	Non-Switch	-0.364	-0.049	-0.048		(0.442)
		(0.151)	(0.168)	(0.136)		
Gym Membership	New Medicare	-0.095	0.129	-0.247	-0.024	0.158
	/Switch	(0.215)	(0.263)	(0.178)	(0.275)	
	Non-Switch	0.180	-0.231	-0.156		(0.273)
		(0.230)	(0.280)	(0.213)		
Routine Eye Exam	New Medicare	-0.977	-0.016	0.274	0.227	-0.018
	/Switch	(0.328)	(0.372)	(0.300)	(0.380)	
	Non-Switch	-0.742	0.124	0.505		(0.326)
		(0.284)	(0.316)	(0.268)		
Routine Hearing Exam	New Medicare	0.590	-0.173	0.002	-0.449	-0.448
	/Switch	(0.206)	(0.228)	(0.173)	(0.274)	
	Non-Switch	0.582	0.202	-0.443		(0.263)
		(0.225)	(0.246)	(0.221)		
HMO	New Medicare	-1.747	0.490	-0.398	0.990	0.981
	/Switch	(0.553)	(0.913)	(0.521)	(1.026)	
	Non-Switch	-1.754	-0.102	-0.910		(0.225)
		(0.680)	(1.017)	(0.619)		
Private-Fee-For-Service	New Medicare	-1.887	1.095	0.029	-8.173	-
	/Switch	(0.697)	(0.983)	(0.617)	(6.540)	
	Non-Switch	-2.911	-0.581	-4.206		
		(2.827)	(2.709)	(2.425)		
Switching Cost		0.172	-0.021	-0.361		-4.488
		(0.192)	(0.231)	(0.171)		(1.010)

Note: The common effect for the dummy variable for Private-Fee-For-Service plans is absorbed by the fixed effects included in the estimating equation (7). Standard errors are in parentheses.

Table A13: Estimates for Parameters of Preference Heterogeneity for the Model with the Full Interaction

	Estimates	Standard Error
Switch	-4.488	(1.010)
Switch x Phy/Cog	0.172	(0.192)
Switch x V/H	-0.021	(0.231)
Switch x HCC Score	-0.361	(0.171)
Switch x J	0.448	(0.523)
Switch x J-squared	-1.039	(0.397)
MA x Phy/Cog	1.882	(0.603)
MA x V/H	-0.027	(0.942)
MA x HCC Score	0.384	(0.558)
MA x MA Last Year x Year 2001	-0.678	(1.018)
MA x MA Last Year x Year 2002	-0.606	(1.018)
MA x MA Last Year x Year 2003	-0.734	(1.030)
MA x MA Last Year x Year 2004	-0.947	(1.036)
MA x MA Last Year x Year 2005	-0.709	(1.030)
MA x New Medicare Beneficiary x Year 2001	-1.691	(1.017)
MA x New Medicare Beneficiary x Year 2002	-1.810	(1.019)
MA x New Medicare Beneficiary x Year 2003	-2.526	(1.019)
MA x New Medicare Beneficiary x Year 2004	-2.556	(1.017)
MA x New Medicare Beneficiary x Year 2005	-2.396	(1.016)

Note: Standard errors are in parentheses.

Table A14: Estimates for Parameters for Common Effects for the Model with the Full Interaction

	Estimates	Standard Error
Premium	-1.023	(0.159)
Preventive Dental Coverage	-0.478	(0.164)
Comprehensive Dental Coverage	0.803	(0.306)
Copay for Outpatient Clinic	0.389	(0.307)
Missing Value for Copay for Outpatient Clinic	0.022	(0.495)
Routine Hearing Exam	-0.448	(0.263)
Hearing Aids	-0.270	(0.277)
Copay for Prescription Drugs	-0.399	(0.149)
Drug Coverage	0.725	(0.442)
Copay for Primary Care Physician	-0.343	(0.109)
Missing Value for Primary Care Physician	-0.085	(0.233)
Copay for Specialist	-1.446	(0.972)
Missing Value for Copay for Specialist	-0.145	(0.345)
Copay for Skilled Nursing Facility	0.035	(0.266)
Copay for Inpatient Care	0.112	(0.153)
Copay for Inpatient Stay	0.110	(0.293)
Gym Membership	0.158	(0.273)
Routine Eye Exam	-0.018	(0.326)
Eyewear	0.079	(0.162)
Copay for Emergency Care	0.109	(0.100)
Missing Value for Copay for Emergency Care	-0.252	(0.481)
Missing Value for Copay for Prescription Drugs	-0.966	(0.446)
Missing Value for Copay for Skilled Nursing Facility	-0.145	(0.218)
Missing Value for Copay for Inpatient Care	-0.128	(0.175)

Note: Standard errors are in parentheses.

Table A15: Semi-Elasticity of Demand with Respect to Advertising and Premiums for the Model with the Full Interaction

	Advertising per Capita (Unit=1 percent of mean advertising)		Monthly Premium ($1)	
Semi elasticity for...	Estimates	Confidence Interval	Estimates	Confidence Interval
Healthy and New Medicare Beneficiaries	0.248	[0.128 0.377]	-0.836	[-1.090 -0.588]
Unhealthy and New Medicare Beneficiaries	-0.166	[-0.362 0.027]	-1.120	[-1.520 -0.686]
Healthy and Incumbent Medicare Beneficiaries	0.151	[0.065 0.241]	-0.668	[-0.877 -0.513]
Unhealthy and Incumbent Medicare Beneficiaries	-0.118	[-0.262 0.021]	-0.845	[-1.080 -0.561]
Overall Medicare Beneficiaries	0.021	[-0.069 0.117]	-0.741	[-0.914 -0.583]

Note: The reported 95 percent confidence intervals are calculated using 200 bootstrapping simulations based on the estimated parameters and associated standard errors. One percent of average advertising per capita among insurers with positive advertising is $0.0033. In terms of dollar spending, $0.0033 per capita is equivalent to $1,911. We define unhealthy as individuals who have any V/H or Phy/Cog issues.

Table A16: Estimates for Parameters of Preference Heterogeneity for the Model with Additional Demographics

Variables	Individual Type	Phy/Cog	V/H	HCC Score	Self-reported Health	Low Income	Below HS	Switch	Common Effects
Advertising	New Medicare	-0.910	-1.265	0.013	-0.335	-0.359	0.295	1.079	-0.047
	/Switch	(0.306)	(0.521)	(0.263)	(0.220)	(0.219)	(0.250)	(0.473)	
	Non-Switch	0.327	-0.906	-0.077	-0.044	-0.050	0.379		(0.118)
		(0.396)	(0.516)	(0.378)	(0.314)	(0.324)	(0.350)		
Premium	New Medicare	-0.006	-0.163	0.162	-0.375	-0.472	-0.444	0.245	-0.900
	/Switch	(0.204)	(0.258)	(0.189)	(0.171)	(0.191)	(0.226)	(0.234)	
	Non-Switch	0.002	0.040	0.169	0.112	-0.338	-0.121		(0.164)
		(0.164)	(0.184)	(0.154)	(0.139)	(0.134)	(0.150)		
Drug Coverage	New Medicare	-0.147	-0.290	-0.069	0.439	-0.393	-0.337	-0.375	0.961
	/Switch	(0.175)	(0.205)	(0.160)	(0.147)	(0.143)	(0.151)	(0.194)	
	Non-Switch	-0.358	-0.073	0.035	-0.149	-0.156	-0.329		(0.446)
		(0.132)	(0.148)	(0.122)	(0.115)	(0.113)	(0.121)		
Switching Costs		0.070	0.127	-0.056	-0.096	0.255	0.018		-3.467
		(0.134)	(0.163)	(0.111)	(0.114)	(0.111)	(0.116)		(0.201)

Note: Self-reported Health is a dummy that equals 1 if a person's self-reported health is neither "very good" nor "good." Low income is a dummy variable that equals to 1 if a person's income is below $20,000. Below HS is a dummy that equals 1 if a person did not graduate from high school. Standard errors are in parentheses.

Table A17: Estimates for Parameters of Preference Heterogeneity for the Model with Additional Demographics

	Estimates	Standard Error
Switch	-3.467	(0.201)
Switch x Phy/Cog	0.070	(0.134)
Switch x V/H	0.127	(0.163)
Switch x HCC Score	-0.056	(0.111)
Switch x Self-Reported Health	-0.096	(0.114)
Switch x Low Income	0.255	(0.111)
Switch x Below High School	0.018	(0.116)
Switch x J	0.480	(0.515)
Switch x J-squared	-1.063	(0.390)
MA x Phy/Cog	-0.251	(0.141)
MA x V/H	0.299	(0.161)
MA x HCC Score	-0.219	(0.118)
MA x Self-Reported Health	-0.010	(0.120)
MA x Low Income	0.526	(0.119)
MA x Below High School	0.417	(0.123)
MA x MA Last Year x Year 2001	0.738	(0.224)
MA x MA Last Year x Year 2002	0.739	(0.234)
MA x MA Last Year x Year 2003	0.675	(0.249)
MA x MA Last Year x Year 2004	0.494	(0.247)
MA x MA Last Year x Year 2005	0.736	(0.259)
MA x New Medicare Beneficiary x Year 2001	-0.360	(0.220)
MA x New Medicare Beneficiary x Year 2002	-0.516	(0.228)
MA x New Medicare Beneficiary x Year 2003	-1.236	(0.225)
MA x New Medicare Beneficiary x Year 2004	-1.281	(0.208)
MA x New Medicare Beneficiary x Year 2005	-1.125	(0.225)

Note: Standard errors are in parentheses.

Table A18: Estimates for Parameters for Common Effects for the Model with Additional Demographics

	Estimates	Standard Error
Premium	-0.900	(0.164)
Preventive Dental Coverage	-0.518	(0.167)
Comprehensive Dental Coverage	0.823	(0.307)
Copay for Outpatient Clinic	0.279	(0.309)
Missing Value for Copay for Outpatient Clinic	-0.078	(0.496)
Routine Hearing Exam	-0.676	(0.167)
Hearing Aids	-0.255	(0.280)
Copay for Prescription Drugs	-0.478	(0.150)
Drug Coverage	0.961	(0.446)
Copay for Primary Care Physician	-0.357	(0.109)
Missing Value for Primary Care Physician	-0.145	(0.235)
Copay for Specialist	-1.264	(0.971)
Missing Value for Copay for Specialist	-0.082	(0.347)
Copay for Skilled Nursing Facility	-0.022	(0.267)
Copay for Inpatient Care	0.100	(0.154)
Copay for Inpatient Stay	0.102	(0.294)
Gym Membership	-0.050	(0.172)
Routine Eye Exam	0.236	(0.204)
Eyewear	0.115	(0.162)
Copay for Emergency Care	0.119	(0.102)
Missing Value for Copay for Emergency Care	-0.181	(0.487)
Missing Value for Copay for Prescription Drugs	-0.953	(0.450)
Missing Value for Copay for Skilled Nursing Facility	-0.181	(0.220)
Missing Value for Copay for Inpatient Care	-0.129	(0.177)

Note: Standard errors are in parentheses.

Table A19: Semi-Elasticity of Demand with Respect to Advertising and Premiums for the Model with Additional Demographics

	Advertising per Capita (Unit=1 percent of mean advertising)		Monthly Premium ($1)	
Semi elasticity for...	Estimates	Confidence Interval	Estimates	Confidence Interval
Healthy and New Medicare Beneficiaries	0.241	[0.135 0.360]	-0.934	[-1.210 -0.675]
Unhealthy and New Medicare Beneficiaries	-0.184	[-0.416 0.011]	-1.320	[-1.710 -0.940]
Healthy and Incumbent Medicare Beneficiaries	0.140	[0.057 0.230]	-0.765	[-0.956 -0.597]
Unhealthy and Incumbent Medicare Beneficiaries	-0.119	[-0.247 0.027]	-0.922	[-1.130 -0.709]
Overall Medicare Beneficiaries	0.037	[-0.045 0.123]	-0.813	[-0.969 -0.654]

Note: The reported 95 percent confidence intervals are calculated using 200 bootstrapping simulations based on the estimated parameters and associated standard errors. One percent of average advertising per capita among insurers with positive advertising is $0.0033. In terms of dollar spending, $0.0033 per capita is equivalent to $1,911 on average. We define unhealthy as individuals who have V/H or Phy/Cog issues.

Table A20: Estimates for Parameters for the Marginal Cost of Insurance through MA

	(1)		(2)		(3)		(4)	
MC	0.566	(0.154)	0.622	(0.023)	0.682	(0.128)	0.523	(0.017)
MC x Drug Coverage	0.189	(0.045)			0.120	(0.034)		
MC x Copay for Primary Care Physician	0.226	(0.052)			0.051	(0.037)		
MC x Copay for Specialist	-0.749	(0.327)			-0.142	(0.230)		
MC x Copay for Skilled Nursing Facility	-0.016	(0.112)			-0.051	(0.075)		
MC x Copay for Inpatient Care	0.230	(0.103)			0.367	(0.066)		
MC x Copay for Emergency Care	0.110	(0.027)			0.033	(0.023)		
MC x HMO	-0.234	(0.089)			-0.250	(0.072)		
MC x Private-Fee-For-Service	-0.301	(0.120)			-0.104	(0.083)		
Preventive Dental Coverage	0.143	(0.055)	0.206	(0.054)	0.225	(0.054)	0.239	(0.054)
Comprehensive Dental Coverage	0.375	(0.079)	0.399	(0.077)	0.398	(0.077)	0.413	(0.077)
Copay for Outpatient Clinic	-0.254	(0.057)	-0.207	(0.056)	-0.194	(0.056)	-0.194	(0.056)
Routine Hearing Exam	0.040	(0.046)	0.086	(0.043)	0.077	(0.044)	0.079	(0.043)
Hearing Aids	0.200	(0.063)	0.229	(0.062)	0.266	(0.062)	0.260	(0.062)
Copay for Prescription Drugs	-0.230	(0.055)	-0.289	(0.054)	-0.314	(0.054)	-0.320	(0.054)
Drug Coverage	-0.124	(0.213)	0.717	(0.117)	0.090	(0.177)	0.676	(0.116)
Copay for Primary Care Physician	-0.953	(0.227)	-0.008	(0.038)	-0.184	(0.162)	-0.013	(0.038)
Copay for Specialist	2.404	(1.509)	-0.708	(0.221)	-0.381	(1.066)	-0.560	(0.219)
Missing Value for Copay for Specialist	-0.473	(0.620)	-0.282	(0.143)	0.145	(0.520)	-0.216	(0.143)
Copay for Skilled Nursing Facility	0.041	(0.469)	0.130	(0.070)	0.287	(0.318)	0.124	(0.070)
Copay for Inpatient Care	-1.085	(0.436)	-0.149	(0.052)	-1.692	(0.284)	-0.157	(0.052)
Copay for Inpatient Stay	-0.278	(0.099)	-0.336	(0.097)	-0.313	(0.097)	-0.336	(0.097)
Gym Membership	-0.489	(0.044)	-0.530	(0.043)	-0.491	(0.043)	-0.524	(0.043)
Routine Eye Exam	-0.410	(0.060)	-0.475	(0.057)	-0.473	(0.057)	-0.485	(0.056)
Eyewear	-0.046	(0.045)	-0.071	(0.043)	-0.066	(0.043)	-0.056	(0.042)
Copay for Emergency Care	-0.717	(0.122)	-0.226	(0.028)	-0.378	(0.104)	-0.230	(0.028)
Dummy for HMO	-0.832	(0.372)	-1.761	(0.073)	-0.720	(0.305)	-1.741	(0.073)
Dummy for PFFS	1.206	(0.483)	-0.043	(0.082)	0.392	(0.347)	-0.063	(0.082)
IV	TM Cost		TM Cost		N		N	
R-squared	0.345		0.345		0.357		0.347	

Note: All specifications include year dummies, dummies for missing values for copayment amounts for different services, and dummies for the five largest insurers: Blue Cross Blue Shield, Humana, United Healthcare, Secure Horizon, and Kaiser Permanante. Moreover, columns (1) and (3) also include interactions between MC and dummies for missing values for copayment amounts for different services and dummies for the five largest insurers. The sample size is 12,133. Columns (1) and (3) refer to the full model specification. Columns (2) and (4) refer to the estimates excluding interaction terms between FFS and plan characteristics. Standard errors are in parentheses.

Table A21: Testing for Advantageous Selection with Self-Reported Health

Market Type	Baseline		Partial		Full	
Panel 1: Consumers That Are New to Medicare: Pr(Switch to MA| Healthy) - Pr(Switch to MA| Unhealthy)						
Markets with Large Advertising	0.0259	[0.0170 0.0340]	0.0145	[0.0069 0.0219]	0.0155	[0.0049 0.0260]
Markets with Small Advertising	0.0242	[0.0179 0.0300]	0.0229	[0.0170 0.0289]	0.0221	[0.0150 0.0289]
All Markets	0.0264	[0.0190 0.0349]	0.0185	[0.0129 0.0249]	0.0188	[0.0109 0.0270]
Panel 2: Consumers with TM Last Year: Pr(Switch to MA| Healthy) - Pr(Switch to MA| Unhealthy)						
Markets with Large Advertising	0.0055	[0.0040 0.0069]	0.0041	[0.0030 0.0050]	0.0039	[0.0030 0.0050]
Markets with Small Advertising	0.0074	[0.0060 0.0089]	0.0071	[0.0060 0.0080]	0.0071	[0.0060 0.0080]
All Markets	0.0063	[0.0049 0.0080]	0.0053	[0.0039 0.0069]	0.0053	[0.0039 0.0069]
Panel 3: Consumers with MA Last Year: Pr(Switch to different MA| Healthy) - Pr(Switch to different MA|Unhealthy)						
Markets with Large Advertising	-0.0110	[-0.0140 -0.0060]	-0.0130	[-0.0170 -0.0090]	-0.0140	[-0.0180 -0.0090]
Markets with Small Advertising	0.0004	[-0.0020 0.0029]	-0.0000	[-0.0020 0.0020]	-0.0000	[-0.0030 0.0020]
All Markets	-0.0080	[-0.0110 -0.0050]	-0.0100	[-0.0130 -0.0060]	-0.0100	[-0.0140 -0.0060]

Note: An individual with self-reported health of "Excellent" or "Very Good" is defined as healthy. Reported 95 percent confidence intervals are calculated based on 200 bootstrapping simulations.

Table A22: Testing for Advantageous Selection with Predicted TM Expenditure

Market Type	Baseline		Partial		Full	
Panel 1: Consumers That Are New to Medicare: Pr(Switch to MA| Healthy) - Pr(Switch to MA| Unhealthy)						
Markets with Large Advertising	0.0742	[0.0530 0.0999]	0.0463	[0.0240 0.0700]	0.0490	[0.0249 0.0750]
Markets with Small Advertising	0.0358	[0.0199 0.0540]	0.0298	[0.0150 0.0479]	0.0275	[0.0099 0.0450]
All Markets	0.0590	[0.0409 0.0810]	0.0390	[0.0199 0.0609]	0.0399	[0.0209 0.0609]
Panel 2: Consumers with TM Last Year: Pr(Switch to MA| Healthy) - Pr(Switch to MA| Unhealthy)						
Markets with Large Advertising	0.0120	[0.0089 0.0150]	0.0088	[0.0060 0.0120]	0.0088	[0.0060 0.0120]
Markets with Small Advertising	0.0113	[0.0089 0.0140]	0.0105	[0.0079 0.0139]	0.0105	[0.0079 0.0139]
All Markets	0.0117	[0.0089 0.0150]	0.0095	[0.0069 0.0130]	0.0095	[0.0069 0.0120]
Panel 3: Consumers with MA Last Year: Pr(Switch to different MA| Healthy) - Pr(Switch to different MA|Unhealthy)						
Markets with Large Advertising	-0.0090	[-0.0160 -0.0010]	-0.0160	[-0.0250 -0.0080]	-0.0160	[-0.0270 -0.0080]
Markets with Small Advertising	-0.0000	[-0.0060 0.0050]	-0.0020	[-0.0080 0.0040]	-0.0010	[-0.0080 0.0049]
All Markets	-0.0070	[-0.0130 0.0000]	-0.0120	[-0.0200 -0.0050]	-0.0120	[-0.0200 -0.0050]

Note: An individual in a market with small (large) advertising is defined as healthy if his or her predicted TM expenditure is above the median among markets with small (large) advertising. Reported 95 percent confidence intervals are calculated based on 200 bootstrapping simulations.

Table A23: Industry Profits in Counterfactuals Shutting Down Advertising

		Market w/ Small Advertising			Market w/ Large Advertising		
Insurer Type	Variable	Baseline	Partial	Full	Baseline	Partial	Full
Advertising> 0	Industry Profit per Capita ($)	588.0	586.0	586.5	931.3	924.2	931.0
Advertising= 0	Industry Profit per Capita ($)	414.6	415.0	415.6	299.4	303.0	306.7

Note: Industry profit per capita is defined as the sum of annual profits across all plans in a county divided by the number of Medicare beneficiaries (not MA enrollees) in the county. Reported numbers are the averages of industry profit per capita conditional on whether an insurer did any advertising and whether the insurer belonged to "Market w/ Small Ad" or "Market w/ Large Ad."

Table A24: Counterfactual: Changes in Risk Adjustment System on Market Equilibrium with Advertising

	Insurers with zero baseline advertising			Insurers with positive baseline advertising		
	Baseline	Weight=0.9	Weight=0.8	Baseline	Weight=0.9	Weight=0.8
Premium	34.9	34.9	34.7	34.1	34.1	33.0
Advertising per Capita	0	0	0	0.409	0.370	0.349
Market Share	0.0265	0.0265	0.0266	0.0579	0.0579	0.0580

Note: Reported numbers are population-weighed mean of market-level average premiums, advertising per capita, and market shares.

Table A25: Comparison between Plan Characteristics across Borders

	DMAs with Less Advertising		DMAs with More Advertising		T-Test	
	Mean	SD	Mean	SD	Difference	T-stat
Advertising per Capita	0.15	(0.21)	0.40	(0.46)	-0.25	(-12.52)
Premium	0.36	(0.30)	0.36	(0.32)	-0.00	(-0.04)
Preventive Dental Coverage	0.09	(0.27)	0.11	(0.31)	-0.02	(-1.41)
Comprehensive Dental Coverage	0.04	(0.20)	0.04	(0.20)	0.00	(0.09)
Copay for Outpatient Clinic	0.02	(0.21)	0.01	(0.19)	0.00	(0.25)
Routine Hearing Exam	0.51	(0.50)	0.53	(0.50)	-0.02	(-0.68)
Hearing Aids	0.06	(0.24)	0.07	(0.25)	-0.00	(-0.30)
Copay for Prescription Drugs	0.46	(0.54)	0.49	(0.59)	-0.03	(-1.03)
Drug Coverage	0.60	(0.49)	0.63	(0.48)	-0.03	(-1.12)
Copay for Primary Care Physician	1.28	(0.74)	1.22	(0.74)	0.06	(1.40)
Copay for Specialist	0.21	(0.09)	0.19	(0.09)	0.01	(2.38)
Copay for Skilled Nursing Facility	0.48	(0.39)	0.44	(0.40)	0.04	(1.94)
Copay for Inpatient Care	0.17	(0.40)	0.16	(0.37)	0.01	(0.37)
Copay for Inpatient Stay	0.11	(0.23)	0.09	(0.20)	0.01	(1.23)
Gym Membership	0.25	(0.44)	0.28	(0.45)	-0.03	(-1.15)
Routine Eye Exam	0.49	(0.50)	0.53	(0.50)	-0.04	(-1.57)
Eyewear	0.34	(0.47)	0.40	(0.49)	-0.06	(-2.28)
Copay for Emergency Care	4.23	(1.00)	4.21	(1.02)	0.02	(0.34)
HMO	0.59	(0.49)	0.62	(0.49)	-0.03	(-1.15)
Private-Fee-For-Service	0.37	(0.48)	0.34	(0.47)	0.03	(1.15)
Average TM Cost	477.24	(73.06)	495.22	(82.05)	-17.98	(-4.13)
AverageTM Cost in Previous Year	445.66	(71.14)	462.13	(77.52)	-16.47	(-3.95)
County Benchmark	562.40	(48.62)	566.04	(50.75)	-3.64	(-1.31)
AverageTM Cost - County Benchmark	-85.16	(64.33)	-70.82	(65.82)	-14.34	(-3.93)
Observations	609		662		1271	

Source: AdSpender 2001–2005; Medicare Compare Files 2001–2005; CMS SPC Files 2001–2005.
Note: The table is created in the following way. For each insurer-border-year, all plans in the DMA where the insurer spends less on advertising are put in DMAs with Less Advertising, and all plans in the other DMA where the insurer spends more on advertising are put in DMAs with More Advertising.

Table A26: Comparison between Conditional Health Care Costs across Borders

	DMAs with Less Advertising		DMAs with More Advertising		T-Test	
	Mean	SD	Mean	SD	Difference	T-stat
Realized TM Cost for Healthy (level)	289.6	(524.0)	304.1	(563.8)	-14.6	(0.94)
Realized TM Cost for Unhealthy (level)	525.0	(892.9)	588.9	(941.9)	-63.9	(1.99)
Realized TM Cost for Healthy (log)	4.33	(2.004)	4.384	(2.00)	-0.0483	(0.80)
Realized TM Cost for Unhealthy (log)	4.83	(2.126)	5.035	(2.05)	-0.197	(2.64)
Observations	6007		7468		13,457	

Source: MCBS 2001–2005.

Note: An individual is defined as "healthy" if the individual does not have any problems with Phy/Cog or V/H.

Table A27: Comparison between Border and Non-Border Counties

	Non-Border Counties		Border Counties		T-Test	
	Mean	SD	Mean	SD	Difference	T-stat
Advertising per Capita	0.13	(0.31)	0.14	(0.41)	-0.01	(-1.39)
Premium	0.38	(0.37)	0.38	(0.36)	-0.00	(-0.09)
Drug Coverage	0.52	(0.50)	0.53	(0.50)	-0.01	(-1.45)
percent HMO Plan	0.63	(0.48)	0.67	(0.47)	-0.03	(-3.84)
percent PPO Plan	0.04	(0.20)	0.04	(0.20)	0.00	(0.93)
percent PFFS Plan	0.32	(0.47)	0.29	(0.45)	0.03	(3.27)
Number of Insurers	3.10	(2.11)	3.31	(2.64)	-0.21	(-4.55)
Medicare Population (market-level)	0.65	(1.26)	0.59	(0.91)	0.06	(3.25)
percent MA Penetration (market-level)	0.14	(0.12)	0.16	(0.14)	-0.02	(-8.67)
Average Market Share (insurer-market-level)	0.05	(0.06)	0.05	(0.07)	-0.00	(-1.14)
County BenchMark (market-level)	574.71	(75.44)	559.91	(62.46)	14.81	(11.65)
AverageTM Cost (market-level)	493.60	(98.18)	495.72	(101.34)	-2.11	(-1.12)
AverageTM Cost - County Benchmark (market-level)	-81.11	(74.81)	-64.19	(76.38)	-16.92	(-11.86)
Observations	7,657		4,477		12,134	

Source: AdSpender 2001–2005; CMS SPC Files 2001–2005.

Table A28: Mintel Summary Statistics

	Households w/o MA Mail	Households w/ MA Mail	Overall
Number of MA Mailings	0	1.24	0.16
Income = 1 (percent) (lowest)	17.0	20.7	17.4
Income = 2 (percent)	16.3	20.5	16.8
Income = 3 (percent)	15.6	16.7	15.8
Income = 4 (percent)	16.1	15.7	16.0
Income = 5 (percent) (highest)	35.0	26.5	33.9
Zip-code-Level Income ($1000)	48.7	47.3	48.5
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

Source: Mintel Comperemedia 2001–2005.

Table A29: Average Value of Each Health Measure for Each Income Group

	HCC Score	Phy/Cog	V/H
Income = 1 (lowest)	1.229	0.509	0.216
Income = 2	1.120	0.326	0.183
Income = 3	1.041	0.259	0.164
Income = 4	0.978	0.219	0.160
Income = 5 (highest)	0.954	0.195	0.141
Total	1.116	0.362	0.186
Observations	33,128		

Source: MCBS 2001–2005.

Table A30: Targeting with Direct Mail Advertising

	(1)		(2)		(3)		(4)	
Dependent variable:	Number of MA mailings				Switches to MA			
$\mathbf{1}[I_{it}=1]$ (lowest)	0.00521	(0.0113)			0.0218	(0.00419)		
$\mathbf{1}[I_{it}=2]$	0.00882	(0.0121)			0.0285	(0.00543)		
$\mathbf{1}[I_{it}=3]$	-0.00657	(0.0118)			0.0230	(0.00526)		
$\mathbf{1}[I_{it}=4]$ (2nd highest)	-0.00380	(0.0110)			0.0151	(0.00459)		
$Post\times\mathbf{1}[I_{it}=1]$	0.0246	(0.0223)			-0.0110	(0.00585)		
$Post\times\mathbf{1}[I_{it}=2]$	0.00780	(0.0223)			-0.0204	(0.00669)		
$Post\times\mathbf{1}[I_{it}=3]$	0.0771	(0.0266)			-0.0149	(0.00638)		
$Post\times\mathbf{1}[I_{it}=4]$	0.0424	(0.0261)			-0.0111	(0.00644)		
$I_{zip(i),t}$			-0.00017	(0.00016)			-0.00014	(0.00004)
$Post\times I_{zip(i),t}$			-0.00066	(0.00023)			0.000035	(0.00004)
FE: County	Y		Y		Y		Y	
FE: DMA-Year	Y		Y		Y		Y	
FE: Year-Month	Y		Y					
Observations	13,264		13,159		32,981		32,980	
R-squared	0.283		0.280		0.074		0.073	

Note: Standard errors are clustered at the county level. The dummy variable *Post* is defined such that $Post=\mathbf{1}[t\geq Oct\ 2003]$ for columns (1) and (2), and $Post=\mathbf{1}[t\geq 2004]$ for columns (3) and (4). All specifications include other control variables discussed in C.

Table A31: Complete List of Plan Characteristics

Characteristic	Unit	Description
Premium	$100	Monthly
Preventive Dental Coverage	Dummy Variable	If offered, equal to 1
Comprehensive Dental Coverage	Dummy Variable	If offered, equal to 1
Routine Hearing Exam	Dummy Variable	If offered, equal to 1
Hearing Aids	Dummy Variable	If offered, equal to 1
Drug Coverage	Dummy Variable	If offered, equal to 1
Copay for Prescription Drugs	$10	30-day supply
Copay for Outpatient Clinic	$10	Per visit
Copay for Primary Care Physician	$10	Per visit
Copay for Specialist	$100	Per visit
Copay for Skilled Nursing Facility	$100	Per day over Medicare-covered stay
Copay for Inpatient Care	$100	Per day over Medicare-covered stay
Copay for Inpatient Stay	$1,000	Per stay
Copay for Emergency Care	$10	Per visit
Gym Membership	Dummy Variable	If offered, equal to 1
Routine Eye Exam	Dummy Variable	If offered, equal to 1
Eyewear	Dummy Variable	If offered, equal to 1
Missing Value for Copay for Emergency Care	Dummy Variable	-
Missing Value for Copay for Outpatient Clinic	Dummy Variable	-
Missing Value for Primary Care Physician	Dummy Variable	-
Missing Value for Copay for Specialist	Dummy Variable	-
Missing Value for Copay for Emergency Care	Dummy Variable	-
Missing Value for Copay for Prescription Drugs	Dummy Variable	-
Missing Value for Copay for Skilled Nursing Facility	Dummy Variable	-
Missing Value for Copay for Inpatient Care	Dummy Variable	-
HMO	Dummy Variable	Network type
PPO	Dummy Variable	Network type
Private-Fee-For-Service (PFFS)	Dummy Variable	Network type
Major Insurers	Dummy Variable	Description in the note below

Note: “Major Insurers” is a dummy variable that is equal to the following five largest MA insurers: Blue Cross Blue Shield, Humana, Kaiser Permanante, Secure Horizon, and United Healthcare