Government Advertising in Market-Based Public Programs: Evidence from the Health Insurance Marketplace

Naoki Aizawa and You Suk Kim*

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Abstract

Government marketing activities are often used to increase enrollment in public programs. They are common in *market-based* public programs, in which private firms provide benefits in regulated markets and conduct their own marketing activities. This paper studies government and private marketing activities in the context of the Affordable Care Act health insurance marketplace. Using detailed TV advertising data, we study a key question for designing market-based public programs: should the government engage in marketing activities, or should private firms exclusively engage in marketing activities? We present evidence that government advertising and private advertising are targeted to different geographical areas and provides different messaging content. Then, by exploiting discontinuities in advertising along the borders of local TV markets, we estimate the impact of each of these types of advertising on consumer enrollment. We find that government advertising has a market-expansion effect, increasing the total program enrollment. In contrast, private advertising tends to steal consumers from other insurers, with little net effect on enrollment. Finally, by estimating an equilibrium model of the marketplace, we explore the impact of changing government advertisement spending. We find that an exogenous increase in government advertising increases total program enrollment while reducing inefficient rent-seeking advertising competition among private insurers: a $1 increase in government advertising decreases private advertising by $0.13. Our finding suggests a welfare-enhancing role of government advertising as a market design tool.

JEL Codes: G2, I1, I3, L1, M3.
Keywords: market-based public program, health insurance, government advertising, advertising competition

*Naoki Aizawa: Department of Economics at the University of Wisconsin-Madison, naizawa@wisc.edu. You Suk Kim: Research and Statistics, Board of Governors of the Federal Reserve System, you.kim@frb.gov. We thank Marika Cabral, Liran Einav, Hanming Fang, Serafin Grundl, Jonathan Kolstad, Corina Mommaerts, Matt Notowidigo, Ken Onishi, Elena Patel, Brad Shapiro, Mark Shepard, Amanda Starc, Justin Sydner, Chris Taber, and Joel Waldfogel, as well as many seminar and conference participants for helpful comments. Joel McMurry and Logan Schultheis provided outstanding research assistance. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the staff, by the Board of Governors, or by the Federal Reserve System.

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1 Introduction

The government often conducts marketing and outreach activities for public programs. In *traditional* public programs–such as Medicaid, the Supplemental Nutrition Assistance Program (SNAP), and Supplemental Security Income Program–where the government directly provides the benefit to enrollees, government marketing activities are done partly in response to low take-up among eligible populations. Common explanations for the low take-up are the lack of information about eligibility and transaction costs associated with enrollment (Currie (2006)). Government marketing activities are considered to be one of the most important polices to efficiently deliver public programs by mitigating these choice frictions (Aizer (2007); Finkelstein and Notowidigdo (2019)).

Government marketing activities are also used to advertise *market-based* public programs, where benefits are provided by private firms in regulated markets. Market-based public programs have become common in health insurance, education, and mortgages.[1] In designing these programs, a key question is whether the government should engage in marketing activities for these programs, or whether advertising should be performed exclusively by private firms. In fact, private firms conduct a substantial amount of marketing activities in these programs (e.g., Aizawa and Kim (2018) for health insurance and Hastings et al. (2017) for privatized pension).[2] Government marketing activities can be an effective policy tool if private marketing activities are socially inefficient (e.g., due to rent-seeking advertising competition) or are less effective than the government's efforts to enroll consumers. However, even if private marketing activities are efficient and effective, the government may have different objectives from private firms–for example, redistributive motives–and thus may want to advertise to enroll certain individuals. To our knowledge, no studies address this question despite a large interest in market design of these programs and its relevance to active policy debates. For example, a recent large cut of the federal marketing budget for the Affordable Care Act's (ACA) health insurance marketplace has spurred interest in the effect of government marketing activities on the stability and efficiency of the marketplace.[3]

In this paper, we study the effects of marketing activities by the government (both

[1]Market-based health insurance programs include the Affordable Care Act marketplace, Medicare Advantage, and Medicare Part D. An example for education benefits is a charter school. The Making Home Affordable program (MHAP) was set up in 2009 to help underwater homeowners to modify and refinance their mortgages through private lenders. The federal government's advertising on the MHAP cost more than $125 millions (`makinghomeaffordable.gov/press-release/Pages/pr_09242014.aspx`).

[2]Andrabi et al. (2017) and Allende et al. (2019) study marketing activities in education markets.

[3]Before 2018, the federal government spent $100 million annually on marketing for the marketplace, which was comparable to advertising spending by private insurers for the marketplace based on our data in this paper. In 2018, the federal government drastically cut its spending to $10 million.

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federal and state) and private insurers in the ACA health insurance marketplace. Among possible marketing tools, we focus on TV advertising. Advertising is the largest component of government marketing activities, and the Department of Health and Human Services, which is responsible for health programs, typically spends more on adverting than other departments except for the Department of Defense (Kosar (2014)). Moreover, researchers can obtain high-quality and detailed data on TV advertising, compared with other marketing tools. Further, the specific context in which we study government and private advertising–the ACA marketplace–is highly policy relevant given the aforementioned budget cut for federal advertising. We first document how the government and private insurers target their advertising in the marketplace. Then, we estimate the impact of government and private advertising on enrollments. Finally, we examine equilibrium impacts of changing government advertising.

Our analysis exploits detailed TV advertising data from Kantar Media, which allow us to observe all the relevant advertising sponsors in this market. The data also contain rich measures of advertising content, including a video file of each advertisement. This information enables us to classify advertisements into different categories, including whether the advertisement provides specific information such as the availability of financial assistance and the open enrollment period.

We first show suggestive evidence that private advertising is geographically targeted very differently than is government advertising (both federal and state). We find that private advertising is targeted much more toward markets with greater numbers of potential marketplace enrollees or markets where potential enrollees likely have better risk (e.g., markets with expanded Medicaid). In contrast, advertising by the government (both federal and state) is much less correlated with the the size and the demographic composition of potential enrollees population. These patterns are consistent with the view that the government uses advertising to provide information to a broad population, while private advertising is targeted based on their profit incentives. We then document which messages are provided in advertisements. We find that although certain contents (for example, the open enrollment period and financial assistance under the ACA) are commonly discussed by both the government and private insurers, there are also significant differences. Almost a half of private advertisements do not mention keywords related to the marketplace but merely promote a private insurer's brand. These findings are also consistent with the view that the government and private insurers may have different incentives behind their marketing activities.

Using insurer-level enrollment data, we then estimate a model for consumer demand for ACA health plans to study the effectiveness of advertising by the government and pri-

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vate insurers. In our model, we allow advertising by federal and state governments and by private insurers to have have different effects on the decision to purchase health insurance. To address a potential endogeneity concern that advertising may be targeted to certain markets based on unobserved characteristics, we exploit the discontinuity in advertising spending along the borders of local TV markets (e.g., Shapiro (2018), Spenkuch and Toniatti (2018), and Moshary (2017)). We find that government advertising, especially by the federal government, has a market-expansion effect, increasing overall enrollment for the marketplace. Quantitatively, the demand elasticity with respect to government advertising is about 0.04. This magnitude is comparable to findings for advertising by private firms for various products studied by Shapiro et al. (2019) as well as health insurance (Aizawa and Kim (2018)). In contrast, although private advertising increases enrollment for insurers conducting advertising, it just leads to reallocation of enrollees among insurers with a limited market-expansion effect. This is consistent with the view that advertising from different companies just results in business stealing without expanding the total number of individuals enrolling for ACA health plans. Moreover, we find little complementarity between government and private adverting with respect to their impacts on consumer demand. These results suggest that government advertising is more effective than private advertising in reducing transaction costs of consumers to enroll in the marketplace or increasing public awareness of the marketplaces.

We also find that government advertising is more effective in earlier years in the marketplace, when there was likely a much greater share of individuals new to marketplaces. This finding suggests that advertising likely reduces transaction costs of potential buyers of marketplace plans, who were likely uninsured before marketplaces became available. Those potential buyers were unlikely to be very familiar with the process of applying for health insurance.

Using variation in messages in advertisements, we also examine which messages increase consumer take-up. We find that the advertisements by the federal government providing information on financial assistance (e.g., the presence of significant premium subsidies) and the open enrollment period are more effective than other types of advertisements. In contrast, similar messages provided by private advertising are not even effective in increasing an insurer's own demand. Rather, private advertisements without specific ACA-related information–for example, those emphasizing the insurer's own brands or plan quality–are much more effective in increasing its own enrollee.

Finally, we examine how changes in government advertising affect the market equilibrium by taking into account the possibility that private insurers endogenously adjust their marketing activities. For this purpose, we model the supply side of the health insur-

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ance marketplace, where insurers optimally choose the level of advertising spending to maximize their profits. We estimate the perceived marginal benefit of advertising by private insurers by using observed advertising spending and our demand estimates. Then, we conduct counterfactual experiments to simulate the impact of changing government advertisement spending. We find that increasing government advertising by three times from its baseline level leads to an increase in market-level enrollment by 6.2% (1.10 percentage point of potential marketplace enrollee) in markets with large baseline federal advertising spending. In these markets, the increase in federal advertising crowds out private advertising significantly, leading to a decrease in private spending by $0.13 for a dollar increase in federal advertising (or a 15% decrease from its baseline level). We also find that the overall market-level enrollment changes very little regardless of whether we allow private insurers to respond to the change in government advertising. This finding is due to our demand estimate that private advertising mainly steals consumers from competitors and that there is little complementarity between government and private advertising. Of course, private advertising may still improve consumer welfare by inducing consumers to switch toward better plans. However, such welfare gains are likely to be much smaller than welfare gains from increasing program enrollment (i.e., switching from being uninsured to insured).[4] These results suggest that government advertising is a market design tool that can enhance welfare in market-based programs.

Our research contributes to three strands of the literature. First, this paper contributes to an active literature on government interventions that increase take-up of public programs. Several studies evaluate marketing and outreach activity designs for public programs. Aizer (2007) explores the effectiveness of a California outreach campaign on Medicaid take-up. More recently, Finkelstein and Notowidigdo (2019) study a randomized experiment to understand the effectiveness of information provision for SNAP eligibility.[5] These papers focus on the effectiveness of government outreach in traditional welfare programs, whereas we focus on designs of marketing and outreach by the government in a *market-based* public program. Very recently, Domurat et al. (2019) and Goldin et al. (2019) study randomized experiments of direct mailings with information on the marketplace the government sent to specific populations.[6] Our study complements these papers by studying marketing activities by not only the government but also private insurers.

[4]This is consistent with findings in related literature (e.g., Finkelstein et al. (2019)) in part because the marketplace regulates minimum quality of plans.

[5]See also Hastings and Weinstein (2008) who study the importance of outreach in public schools.

[6]Domurat et al. (2019) consider individuals who had accounts in marketplaces but did not sign up. Goldin et al. (2019) consider individuals those who paid individual mandate tax penalty in the previous year.

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Moreover, we focus on TV advertising, which is a marketing activity targeted at a broader population. Ours is the first to study equilibrium effects of government marketing activities, taking into account endogenous responses by private insurers.

Second, this paper is related to the literature investigating the market design of health insurance markets. The literature has extensively focused on pricing/product regulations and subsidy designs/risk adjustment–e.g., Hackmann et al. (2015) and Handel et al. (2015) for pricing regulations; Shepard (2016) and Ho and Lee (2019) for medical network provider regulations; Brown et al. (2014) for risk adjustment; and Cabral et al. (2018), Curto et al. (2019), Duggan et al. (2016), Tebaldi (2017), and Polyakova and Ryan (2019) for capitation payments or subsidy designs.

We contribute to this literature by studying an equally important yet under-studied policy design tool: a design of marketing and outreach activities by the government. In fact, several studies (Cebul et al. (2011) and Aizawa and Kim (2018)) argue the importance of marketing activities by private insurers in determining market outcomes in health insurance markets. Choice frictions are especially relevant in health insurance (Handel (2013); Bhargava et al. (2017)). A few recent studies in the health policy literature (Karaca-Mandic et al. (2017) and Gollust et al. (2018)) document a negative association between government advertising and the number of uninsured individuals in the first year of the ACA.[7] One of our main contributions is to estimate both demand and supply-sides of the marketplace to assess equilibrium implications of marketing activities. Using detailed advertising and enrollment data, we provide the first estimate of the demand model that characterizes the impact of advertising on the insurer choice, its heterogeneous effect, the effect of advertising content, and business stealing/spillover effects of private advertising. Our empirical strategy explicitly addresses endogeneity of advertising by exploiting an advertising market border identification approach. Moreover, by estimating the supply-side of the market, we study how private insurers compete each other via advertising. Then, we show how the government advertising affects private advertising competition in equilibrium.

Third, this paper contributes to the literature on advertising. A growing number of studies evaluate advertising by private companies in an equilibrium framework for different contexts: Goeree (2008) for the personal computer; Dubois et al. (2018) for junk food; Gordon and Hartmann (2016), Moshary (2017), and Spenkuch and Toniatti (2018) for U.S. elections; Shapiro (2018) and Sinkinson and Starc (2018) for pharmaceuticals; and Hastings et al. (2017) for privatized pensions. More recently, Shapiro et al. (2019) estimate

[7] Barry et al. (2018) also analyze the content of ACA advertising over time and discuss whether it is designed to attract young and healthy individuals.

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the effect of advertising on consumer demand in a variety of products based on the border identification approach. Finally, our analysis is also related to the growing literature evaluating the effectiveness of advertising content (e.g., Bertrand et al. (2010)).

The paper proceeds as follows. Section 2 provides an institutional background on the marketplace; Section 3 introduces our main data and shows descriptive evidence. Section 4 presents our demand model and its estimates; Section 5 discusses our supply-side model and counterfactual simulation results. Finally, Section 6 concludes.

2 Background on the Health Insurance Marketplace

The health insurance marketplace is a federal/state-based health insurance program for the non-elderly (people younger than 65) in the United States. It was established in 2014 as a part of the ACA. The marketplace is designed to provide health insurance for non-elderly uninsured individuals, which was close to 20% of the population before the ACA. In the marketplace, private insurers offer health plans, and the federal government offers premium and cost-sharing subsidies to low-income enrollees. Each plan is categorized based on a "metal" ranking, which provides different levels of generosity: Bronze, Silver, Gold, and Platinum. Individuals can decide to purchase health plans during the open enrollment period, typically starting in the beginning of October of the preceding year when the new coverage begins. Each plan is an annual contract, and individuals need to re-enroll every year.

Rating Regions. Each state is divided into geographical rating regions, which are groups of counties or zip codes. Within each geographical rating region, insurers are not allowed to explicitly discriminate their pricing and product offerings based on the consumer's health status. Insurers can still charge different premiums based on an individual's age and smoking status under a pre-specified rule: specifically, the maximum premium ratio between the oldest (age 64) and the youngest (age 18) must be equal to a factor of 3; the smoker's insurance premium is 1.5 times as high as that for non-smokers.

Consumer Subsidies. Consumers are offered premium subsidies from the federal government. The amount of the subsidy depends on the household income. A household with a lower income receives a more generous subsidy. Moreover, it depends on whether the state government expanded Medicaid. If Medicaid is expanded, subsidies are given to households with income between 138% and 400% of the federal poverty level (FPL); households with income below 138% of the FPL qualify for Medicaid. Without Medicaid

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expansion, subsidies are given to households with income between 100% and 400% of the FPL; households with incomes below 100% of the FPL can still purchase a plan from the marketplace without subsidies.[8] Consumers purchasing Silver plans also receive income-dependent cost-sharing subsidies. Overall, the government spends close to $40 billion per year on premium and cost-sharing subsidies.

Risk Adjustment System. To mitigate insurers' incentives to selectively enroll healthy, low-cost individuals (i.e., risk selection), the ACA uses a risk adjustment system. This is a budget-neutral transfer scheme in which insurers receive transfers based on the relative (within state) risk composition of their insured population. The risk of an enrollee is assessed based on a risk score, which is calculated based on a variety of concurrent diagnoses. Budget neutrality implies that insurers who enroll relatively healthier individuals make payments to insurers who cover less healthy populations.[9, 10]

Because the risk scores are based on observed enrollee characteristics, these scores may not perfectly reflect a consumer's true risk. Previous work has documented that eliminating incentives for insurers to select on risk is difficult in the context of Medicare Advantage (e.g., Brown et al. (2014); Newhouse et al. (2015)). Therefore, it is possible that insurers may still gain from risk selection despite the presence of risk adjustment system.

Marketplace Administration and Marketing. State governments have three options to administer marketplaces. First, they can participate in the federally facilitated marketplace, which is operated by the Department of Health and Human Services (HHS). Second, they can create their own marketplaces (state marketplaces). Third, they can partner with the federal marketplace (partnership marketplaces). Each of these three options provides state governments with different levels of freedom in designing their marketplaces. For example, under different models, states are given different levels of ability to tailor consumer outreach and assistance to their populations. Under the state marketplace model, states assume full responsibility for operating consumer assistance, including marketing through TV advertising. Their marketing expenses are largely funded

[8] The ACA also imposes the tax penalty to the uninsured, known as the individual mandate. Households with income less than 100% of the FPL will be exempt from the individual mandate if the state government does not expand Medicaid.

[9] This design is different from other health insurance markets, such as Medicare Advantage, where the amount of risk adjustment transfers does not depend on relative composition of enrollees' health risks across insurers in the same market. In non-ACA health insurance markets, an insurer's payment from a risk adjustment system typically depends only on its own enrollees' risk profile, regardless of the risk compositions of enrollees of other insurers.

[10] The ACA previously incorporated two additional features into the risk adjustment program: reinsurance and risk corridors. However, both were terminated by the end of 2016.

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by the federal government. In the federally facilitated marketplace, however, the federal government is responsible for conducting these activities. In the partnership marketplace, enrollment is conducted through the central website for the federally facilitated marketplace (HealthCare.gov), but the state retains the outreach function.

3 Data and Descriptive Evidence

This paper combines data from multiple sources. We use the enrollment data for 2014–2018 from the Centers for Medicare and Medicaid Services (CMS) to construct market shares for insurers. We obtain detailed information on advertising from Kantar Media. This data set provides occurrence-level TV advertising information on local and national advertisements by private insurers and federal and state governments for 2013–2018.

3.1 Data Sources

3.1.1 Firm- and Market-Level Data

Our analysis combines enrollment data of federally facilitated and partnership marketplaces and the two largest state marketplaces from California and New York. Each year, the CMS releases enrollment data for 38 states in federally facilitated or partnership marketplaces. The data provide information on enrollment at the insurer-county level for each year from 2014 to 2018 and its breakdown by gender, age, household income, and smoking status. In addition, we also obtain enrollment data from state marketplaces in California and New York. These data provide total enrollments for each insurer-county-year but do not include totals by demographic group.

To construct market shares for each insurer in a county, we obtain county-level market size from the American Community Survey (ACS). Following Tebaldi (2017) and Polyakova and Ryan (2019), we define the market size of each county as the sum of the number of uninsured individuals and the number of individuals who individually purchased health insurance instead of obtaining it from their employers. This number measures the number of potential marketplace enrollees. We also obtain county-level health characteristics, such as the fraction of populations with poor or fair self-reported health from the County Health Rankings by the Robert Wood Johnson Foundation (CHR).[11]

[11] Note that the health measures reported in CHR in each survey year are based on outcomes in previous years. For example, the county-level self-reported health status reported in survey years from 2016 to 2018 is based on actual self-reported health status as of two years before. In other words, the data from 2016 to 2018 provides information about self-reported status from 2014 to 2016. Because the data do not provide information about health status in 2017 or later, we assign health status for 2016 and later to those later years.

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3.1.2 Advertising Data

Our advertising data are from the Campaign Media Analysis Group at Kantar Media. The data provide detailed characteristics of advertising related to health insurance, particularly the ACA health insurance marketplace, at the occurrence level. There are two unique aspects of the data that make it suitable for our research. First, the data allow us to identify which entity (the federal government, state governments, or private insurers) sponsored a given piece of advertisement. Moreover, the data contain information about ACA-related political advertising and advertising by insurance navigators, who help consumers with enrolling for the marketplace. Second, we can access a video file of each advertisement in the data. This allows us to characterize the message content of each advertisement and see how content varies across sponsors.

The main measure of our analysis is each sponsor's per-capita advertising spending at a local TV market (usually called a designated market area (DMA)), which typically consists of a major city and surrounding counties.[12] We create this measure by combining spending on advertisements in local DMA-level TV channels and for those in national network TV.[13]

Identifying Marketplace-Related Advertisement We exploit the detailed information in the database to identify which advertisements are related to marketplaces. Using Amazon Web Services, we transcribed each advertisement and examined its content based on keywords. This allows us to identify whether an advertisement (i) is related to the marketplace, (ii) merely promotes a private insurer's brand, or (iii) is related to health insurance but not about the marketplaces (i.e. Medicare). In our analyses, we consider types (i) and (ii) and exclude type (iii).

Depending on advertisement sponsors, we use a slightly different algorithm to classify each advertisement into type (i), (ii), or (iii). First, for advertisements by the federal gov-

We do not believe that our results are sensitive to the way we construct the county-level health measure because actual county-based health status is likely to be very persistent over time. We also experimented with an alternative way to construct the health measure by calculating the average health status for each county across years. We find our main results robust.

[12]We also observe gross rating points (GRP), which is often used in other research on advertising. However, we believe that per-capita advertising spending is more suitable for this paper. We observe GRPs only for a subset of advertisements in the data, whereas we observe dollar spending for all advertisements. Further, GRPs measure the share of the general population exposed to a particular advertisement. However, because the ACA marketplace is mainly relevant for a very particular set of the population, GRPs may misrepresent how much of the population is exposed to a relevant advertisement.

[13]Specifically, we sum two ratios: (i) the ratio of a sponsor's total spending in local TV channels in a DMA to the DMA-level market size and (ii) the ratio of a sponsor's national network TV spending to the national market size. The way in which we construct the per-capita spending is similar to Sinkinson and Starc (2018).

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ernment, we initially select those advertisements with the HHS as their sponsor names.[14] Among this set, we identify marketplace-related advertisements (type (i)) by checking the transcript for mentions of "HealthCare.gov." Because there are about only 100 distinct advertisements by the HHS, we verified our classification by watching individual advertisements. Type (ii) does not exist for federal advertising, and we exclude type (iii) –for example, ones in which HHS promotes Medicare.

Second, for advertising by state governments, we initially select those advertisements with sponsor names that match names of state marketplaces such as Covered California and New York State of Health. Among this set, we again identified marketplace-related advertisements (type (i)) by checking their transcripts and individual advertisement videos visually. Type (ii) advertisements from state governments do not exist, and we exclude type (iii) advertisements from state governments–for example, those about Children's Health Insurance Programs.

Third, for private advertising, we rely only on transcripts because it is not feasible to watch each of thousands of distinct advertisements by private insurers. We initially exclude advertisements with type (iii) keywords such as "Medicare Advantage," "Medicare Part D," "Medigap," and "employer-sponsored insurance." Among the remaining advertisements, we identify type (i) with keywords related to the marketplace such as "open enrollment," and "financial assistance." The remainder is classified as type (ii).

3.2 Summary Statistics

First, we document the volume of marketplace advertising by each sponsor type. Figure 1 reports monthly time-series patterns of advertising spending by governments and insurers. We find that private ACA-related advertising is somewhat larger than advertising by state and federal governments. However, the magnitude of total government advertising (federal and state combined) is still sizable, generally more than $100 million per year. This is comparable to total private advertising for health insurance (ACA and non-ACA advertisements combined). Regardless of sponsors, most advertisements were placed around the open enrollment periods of the marketplace.

In 2017, the federal government decided to cut its total marketing budget for 2018 to only $10 million. As seen in Figure 1, TV advertising in 2018 by the federal government is reduced to almost zero. At the same time, there is a large increase in both ACA and non-ACA private advertising. As a result, the total volume of advertising associated with

[14] We also checked whether there are other federal sponsors that would place marketplace-related advertisements. However, federal advertising seems to be done exclusively by the HHS.

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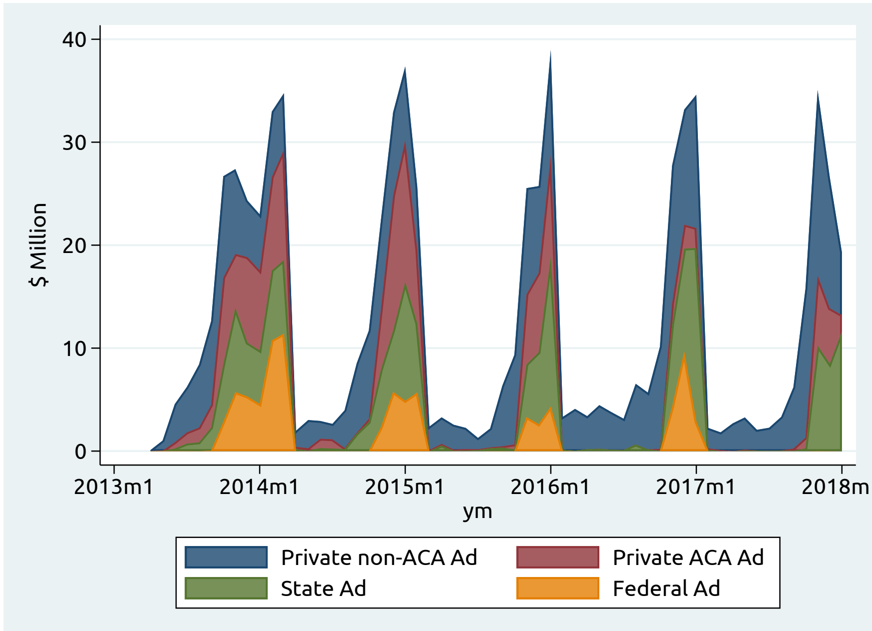
Figure 1: Time Series of Advertising Spending



Note: This figure plots monthly expenditures in millions for TV advertisements by the federal and state governments and private insurers' ACA-related and non-ACA-related advertisements. Data source: Kantar Media.

marketplaces is roughly unchanged from 2017. Because there are many other changes that may induce an increase in private advertising in 2018, we do not interpret this relationship as causal. However, this data pattern motivates us to study interactions between government and private advertising in Section 5.

Figures 2 show DMAs in which different sponsors advertised for the 2014 open enrollment period. The figures show that federal and state governments advertised in very different DMAs. This is simply because state governments advertised mainly in DMAs with state or partnership marketplaces, while the federal government advertised mainly in DMAs with federally facilitated marketplaces. The same figure also shows that the distribution of government and private advertising spending differs significantly across DMAs. For example, compared with private insurers, the federal government advertises extensively in Arizona and Florida.

Table 1 presents summary statistics on characteristics of markets, split by the intensity of federal, state, and private advertising spending, respectively. For columns regarding state advertising ((3) and (4)), we restricted the sample to DMAs that include counties from states responsible for marketing the marketplace. The table shows that government and private advertising spending are not perfectly correlated with each other. Comparing

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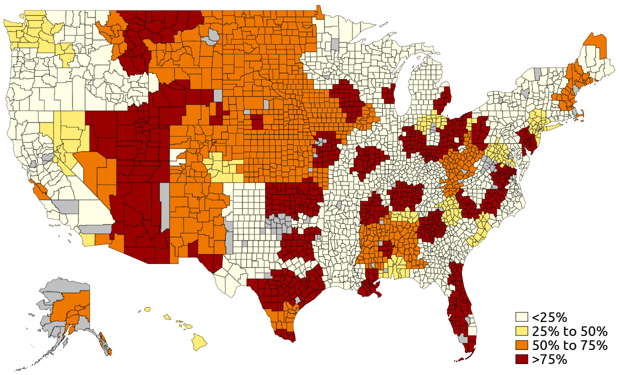
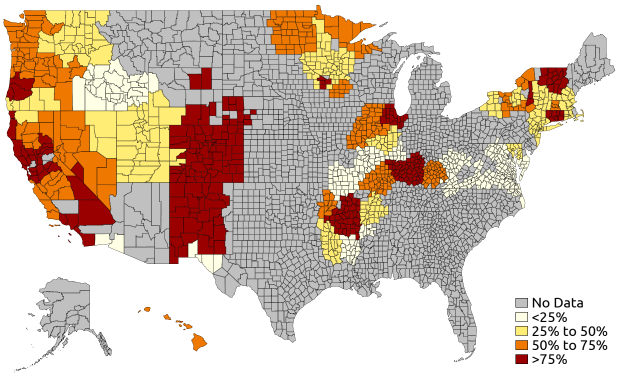
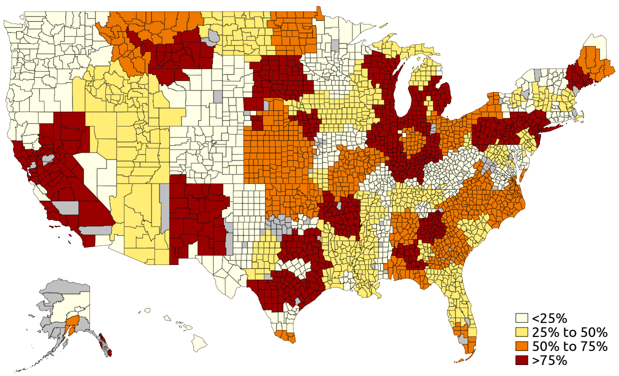
Figure 2: Geographical Patterns of Government and Private Advertising



(a) Fed Ad per Capita



(b) State Ad per Capita



(c) Private Ad per Capita

Note: This figure plots geographical patterns of advertisements by the federal and state governments (Panels (a) and (b)) and private insurers (Panel (c)). In each panel, a DMA is highlighted in different colors depending on relative advertising spending. The larger the total spending in an DMA is, the darker its color is. DMAs for which state governments are not responsible for marketing are highlighted in grey and denoted as "No Data" in Panel (b). Data source: Kantar Media.

Columns (1) and (2), it is apparent that private advertising spending is lower in DMAs with above-median federal advertising spending. The table also shows that almost all DMAs where state governments directly advertised the marketplace have Medicaid expanded (comparing Columns (3) and (4) with other columns).[15] Private advertising is also larger in those DMAs. Moreover, regardless of advertising sponsors, advertising is larger in DMAs with a greater market size; private advertising is larger for DMAs with a greater number of insurers, whereas either federal and state advertising does not seem highly correlated with the number of insurers in a DMA. Lastly, demographic characteristics considered for this table do not seem highly correlated with any types of advertis-

[15]Every state with positive advertisement spending also expanded Medicaid. The Medicaid dummy is not equal to one in Columns (3) or (4) because some DMAs include counties from states with and without expanded Medicaid.

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Table 1: Summary Statistics at DMA-Year Level

	By Fed Ad Spend		By State Ad Spend		By Priv Ad Spend	
	(1)	(2)	(3)	(4)	(5)	(6)
	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median
Fed Ad per Capita ($)	0.14	0.50	0.27	0.17	0.25	0.35
State Ad per Capita ($)	0.41	0.22	0.19	1.88	0.26	0.40
Priv Ad per Capita ($)	1.16	0.94	0.76	1.53	0.11	2.02
Medicaid Expanded	0.66	0.64	0.94	0.98	0.61	0.69
Market Size (100,000)	1.99	2.95	2.00	3.62	1.26	3.57
No. of Insurers	3.55	3.37	3.46	3.79	2.89	4.06
Share: Income $\leq$ 138% of FPL	0.23	0.23	0.23	0.19	0.23	0.23
Share: Age $\geq$ 55	0.18	0.18	0.18	0.19	0.18	0.18
Share: Poor or Fair Health	0.17	0.17	0.17	0.16	0.18	0.17
N. Obs.	434	350	124	124	392	392

Note: This table reports summary statistics of market characteristics depending on federal, state, and private advertising spending. Odd (even)-numbered columns present characteristics of DMAs below (above) the medians of the three types of advertising. We restricted the sample year up to 2017 for this table because there is no federal advertising in 2018, although our demand estimation in Section 4 uses the sample up to 2018. For Columns (3) and (4), we restricted the sample to DMAs that include counties from states reponsible for marketing the marketplace. The number of observations is not balanced for Columns (1) and (2) because there are many DMAs that received zero local federal advertising. "Medicaid Expanded" is the fraction of markets where Medicaid was expanded under the ACA. "Share: Income$\leq$138% of FPL" is the share of individuals with incomes below or equal to 138% of FPL. "Share: Age$\geq$55" is the share of individuals aged 55 or above. "Share: Poor or Fair Health" is the share of individuals with poor or fair self-reported health. Data source: Kantar Media.

ing. However, this result does not rule out the possibility that advertising is still targeted based on these demographic variables if these demographic variables are correlated with other factors that are also taken into account for targeting. We use DMA-level regressions to study more systemically how advertising is targeted in Section 3.3.

Table 2 shows summary statistics of advertisement content depending on sponsor types (federal and state governments, and private insurers). With transcripts of advertisements in our sample, we first consider the following advertisement contents: whether an advertisement mentions the open enrollment period, financial assistance under the ACA, the healthcare reform, being uninsured, or the financial penalty of not having health insurance. We then tabulate the proportion of advertisements that mention keywords related to each topic and present proportions by year and sponsor. Details on how these variables are constructed are in Appendix C.

We find that although certain contents (for example, the open enrollment period and financial assistance under the ACA) are commonly discussed by all sponsors, there are significant differences in contents between government and private advertisements. For example, almost a half of private advertisements do not mention keywords related to the

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Table 2: Ad Contents

	(1) Private	(2) Federal	(3) State
Share: Any ACA-related	0.42	1.00	1.00
Share: Open Enrollment	0.25	0.22	0.21
Share: Financial Assistance	0.25	0.31	0.39
Share: Healthcare Reform	0.16	0.18	0.02
Share: Uninsured	0.02	0.03	0.11
Share: Penalty	0.10	0.00	0.02
N. Obs.	890,892	249,037	444,182

Note: This table reports summary statistics of messages in advertisements by private insurers and the federal and state governments for 2014–2018. The unit of observation is each advertisement occurence, and reported numbers are averages weighted by each advertisemtn's dollar cost. Numbers in each column do not necessarily sum up to one because each advertisement can have multiple messages. Data source: Kantar Media.

marketplace, whereas all federal and state advertisements are ACA-related (by definition).[16] These private advertisements without ACA-related contents usually seem to promote an insurer's brands, quality, and various insurance options provided by its plans. On the other hand, even when federal or state advertisements do not provide *specific* contents defined above, they still inform consumers of presence of marketplaces, always showing the web addresses of the federal and state marketplaces.

This difference in contents between governments and private insurers is indicative of their different incentives. The large fraction of private advertisements unrelated to the marketplace reflects that the goal of private advertising is to maximize an insurer's own profit. This may not be always aligned with the government's likely goal to increase total enrollment in the marketplace. For example, such private advertisements unrelated to the marketplace may be effective in an increasing enrollment for an insurer at the expense of enrollment for other insurers, with only a limited net impact on the total marketplace enrollment. In contrast, the government may aim to reduce transaction costs of enrolling in the marketplace by providing specific information. For this reason, we expect that advertisements from different sponsors providing different contents have different effects on demand, which we will examine more closely in our demand analysis in Section 4.

3.3 Suggestive Evidence for Targeting Advertising

We now carry out preliminary analyses to explore how advertising by governments and private insurers are geographically targeted. We investigate how advertisement spending

[16]We also checked a random sample of private advertisements visually whether they show the web address of the marketplace (e.g. Healthcare.gov), but none of them, including even ACA-related ones, do. In contrast, federal and state advertisements always show the web address of their marketplaces.

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is correlated with DMA characteristics by estimating the following regression:

$$\ln(1 + ad^{\tau}_{mt}) = X_{mt}\gamma + \xi_t + \epsilon_{mt}. \tag{1}$$

The dependent variable ad^{τ}_{mt} represents advertising spending per capita by sponsor type $\tau \in \{f, s, p\}$, which is the federal government (f), state government (s), or private insurer (p). Explanatory variables X_{mt} include various DMA-level characteristics considered in Table 1. ξ_t refers to a year fixed effect. Although we are reluctant to view our estimates as causal, we aim to learn which market characteristics are associated with greater advertising spending by sponsor type.

Table 3: Targeting of Advertising: Aggregate Results

	(1) Federal	(2) State	(3) Private (All)	(4) Private (ACA)
Share: Income $\leq$ 138% of FPL (%)	-0.001	-0.036***	0.016**	0.008**
	(0.002)	(0.008)	(0.008)	(0.003)
Medicaid Expanded=1	-0.098*		0.545**	0.195*
	(0.058)		(0.224)	(0.099)
Medicaid Expanded=1 $\times$ Share: Income $\leq$ 138% of FPL (%)	0.003		-0.018**	-0.005
	(0.002)		(0.009)	(0.005)
Share: Age $\geq$ 55 (%)	0.001	-0.007	0.017**	0.003
	(0.002)	(0.014)	(0.008)	(0.004)
Share: Poor or Fair Health (%)	0.002	0.017	-0.008	-0.002
	(0.002)	(0.011)	(0.008)	(0.005)
No. of Insurers	0.017***	0.091***	0.059***	0.019***
	(0.006)	(0.028)	(0.015)	(0.007)
Log of Market Size	0.029***	-0.038	0.147***	0.074***
	(0.008)	(0.054)	(0.025)	(0.013)
Year FE	Y	Y	Y	Y
N. Obs.	784	302	983	983
Adj. R^2	0.148	0.186	0.212	0.210

Note: This table reports estimates of the coefficients in Equation (1). Because there is no federal advertising spending in 2018, we restricted our sample years to 2014–2017 for Column (1). For Column (2), we restricted the sample to DMAs that include counties from states for which states are reponsible for marketing the marketplace. For the same column, we do not include the dummy variable for Medicaid expansion because every state with positive advertisement spending expanded Mediciad. Standard errors are in parentheses and clustered at the DMA level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

Table 3 presents estimates of the regression in Equation (1). Columns (1) and (2) report results for federal and state advertising, respectively. Column (3) presents results for all private advertising, and Column (4) restricts private advertising to ACA-related content. We find that government advertising is not particularly targeted based on DMA-level demographic characteristics other than the number of insurers and the market size, whereas private advertising varies more with demographic characteristics.

This may reflect different objectives of the government and private insurers. While

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private insurers likely advertise more in DMAs with higher returns from advertising, the government's objective is not necessarily aligned with the profit motive. For example, we find that Medicaid expansion is associated with 72% ($\simeq 100 * (\exp(0.545) - 1)$) more total private advertising. In DMAs without Medicaid expansion, one standard deviation increase in the share of individuals with incomes below or equal to 138% of the FPL (6.4 pp) is associated with 10% more total private advertising. However, such a correlation disappears among DMAs that expanded Medicaid. Moreover, private insurers also tend to target DMAs with larger shares of older individuals (aged 55 or above).

To interpret these results, we hypothesize that private insurers want to advertise in DMAs where a greater number of consumers are more responsive to advertising or/and more profitable to insure. Private insurers may target DMAs with Medicaid expansion (conditional on the market size) because Medicaid can make the average risk pool of the marketplace less risky by absorbing low-income populations, who are more likely to be high-risk.[17] In DMAs with Medicaid expansion, private insurers are less likely to target households with incomes below 138% because they qualify for Medicaid but do not for subsides in the marketplace. In DMAs without Medicaid expansions, however, individuals with incomes between 100% and 138% of the FPL can receive the largest federal subsidies (see Section 2 about Medicaid eligibility). Thus, they are likely responsive to advertising, which we confirm later in our demand analysis (Section 4.3.3). Although these populations could be less healthy, profit-maximizing insurers may target DMAs with more individuals with such income levels to effectively increase the market share. Furthermore, enrolling older consumers can generate a larger profit to insurers in the long run despite their potentially higher costs in the short run.[18] Health plans in the marketplace are available for consumers below age 65; from age 65, these consumers can switch to *private* Medicare benefits. If insurers expect that consumers will remain with them after turning to age 65, they may be interested in attracting older consumers.

In contrast, federal advertising does not systemically vary with the share of low-income individuals, its interaction with Medicaid expansion, or the share of older individuals. Although there is more federal advertisement spending in DMAs without Medicaid expansion, the estimated effect is marginally significant and much smaller in magnitude than that for private advertising. This may represent that the federal government wants to reach out a broader population.

In addition to the demographic variables, we also examine the targeting based on the

[17]See Sen and DeLeire (2018) for evidence that Medicaid expansion improves the risk pool of the marketplaces.

[18]Although older individuals spend more health care and thus cost more to insurers, insurers can still charge a much higher premium to older individuals, which also mitigate insurers' short-run cost.

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share of the population reporting poor or fair health across DMAs, but we do not find statistically significant correlations with advertising by any sponsor.[19] In Appendix D, using the list of message contents from Table 2, we investigate how per-capita advertisement spending for each type of content and sponsor is targeted to different DMAs. We find some evidence of targeting by content type. For example, private advertising emphasizing the penalty of not enrolling in health insurance follows similar patterns to overall private spending, while private advertising that emphasizes the open enrollment period is uncorrelated with DMA demographics.

Taken together, these results suggest that governments and private insurers target advertising to different DMAs. One way to interpret these results is that different sponsors have different objectives. Private insurers seem to target DMAs with individuals who are likely more responsive to advertising and more profitable to insure. The government, on the other hand, may not be profit-maximizing, and thus follows different targeting patterns. We next estimate the impact of advertising on consumer demand to better understand how advertising from different sponsors increases enrollments.

4 The Impact of Advertising on Consumer Demand

4.1 Market-level Analysis

To examine the effect of government and private advertising on consumer demand, we first examine its impact on market-level enrollment in the marketplace. The primary objective of this analysis is to understand whether advertising has any meaningful effects on market expansion. Although advertising could potentially have an impact on Medicaid enrollment, we abstract from such an analysis.[20]

4.1.1 Identification: Border Strategy

In estimating the effects of advertising, endogeneity of advertising is a usual concern. Private insurers may choose to advertise more in markets where expected profits from advertising are large, and they may have higher expected profits in some markets because of unobserved heterogeneity in consumer demand. For example, some insurers may have better brand images in certain markets and thus concentrate their advertising

[19]We also examined other health measures such as health care costs, the fraction of obesity and diabetes, but find similar patterns. These results are available upon request.

[20]Our preliminary analysis suggests that the effect on Medicaid enrollment is likely limited. This result is available upon request.

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campaigns in such markets. In contrast, it is not clear whether the government implements a sophisticated targeting strategy. Even if the government is sophisticated, it is not obvious whether the government targets market with high or low demand for insurance. Depending on how advertising and demand for insurance are correlated, a naive regression of county-level enrollment on advertising may lead to under- or over-estimation of the effects of advertising.

In order to address the endogeneity of advertising, we build on the work by Shapiro (2018), Tuchman (2019), Moshary (2017), Aizawa and Kim (2018), and Spenkuch and Toniatti (2018) and implement a border identification strategy.[21] The border strategy exploits a discontinuity of advertising expenditures across a border between DMAs. This discontinuity arises because the Federal Communications Commission regulations grant media companies local broadcast rights at the DMA level. 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. The border strategy relies on the regulation-induced discontinuities in exposure to advertising across neighboring border counties in the same state but different DMAs.[22]

To implement the border strategy, we first identify pairs of adjacent border counties in the same state that belong to two different DMAs, which are referred to as a border pair. With fixed effects for border pair-by-year, we absorb unobserved heterogeneity in demand that is common for each border pair and year. Using the panel structure of our data, moreover, we additionally include county fixed effects to absorb county-level unobserved heterogeneity in demand that is persistent over time. With the two sets of fixed effects, remaining unobserved heterogeneity is at the level of each county and year within a border pair. Our identifying assumption is that the remaining unobserved heterogeneity is uncorrelated with advertising. In other words, we assume that a growth in advertising spending in a DMA is uncorrelated with changes in county-level unobserved heterogeneity in demand over year.

One important advantage of our border strategy is that it allows us to identify the effect of advertising separately from other ways in which the government or insurers can increase enrollments. For example, the government may conduct outreach activities besides advertising. However, our identification strategy is unlikely to be contaminated by these outreach activities because such activities are not likely to discretely change across

[21]The main idea behind this type of border strategy is already presented in the seminal work by Holmes (1998) and Black (1999). See Li et al. (2020) for the relationship between the border strategy and the Waldfogel instrument (Waldfogel (2003)), which is commonly used in the industrial organization literature.

[22]We only compare border counties in the same state because marketplaces in different states can be very different.

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DMA borders in a way that is correlated with a growth in TV advertising spending.

The identifying assumption for the border strategy is more likely to be plausible if county characteristics are indeed balanced in the cross section. Having balanced county characteristics in either side of the border is not a necessary condition of our identification assumption because we use the panel structure of the data. However, one might expect that counties with similar observed characteristics are likely to have similar trends for unobserved heterogeneity. Indeed, we find that market characteristics are also almost identical between pairs of border counties with different advertising, as discussed in detail in Appendix A.

An important caveat about the border strategy is that estimated effects of advertising are local to border counties. Thus, it might be difficult to extrapolate the estimated effects to non-border counties, which are excluded from the estimation sample. However, we also show in Appendix A that there are only limited observable differences between border and non-border counties, which suggests that estimates based on our border sample are unlikely to be very different from ones based on the entire sample.

4.1.2 Effects of Advertising on Market-level Enrollments

We estimate the following county-level regression:

$$\ln(s_{bct}) = \sum_{k \in K} \ln(1 + ad^{k}_{bm(c)t})\beta_k + \boldsymbol{x_{bct}}\gamma + \xi_{bt} + \xi_{r(c)t} + \xi_c + \epsilon_{bct}. \tag{2}$$

The dependent variable refers to the log of the share of individuals that enrolled in marketplace plans in border pair b, county c, and year t.[23] On the right-hand side, $ad^{k}_{bm(c)t}$ refers to the advertising expenditure of category k per potential marketplace enrollee in border pair b, DMA $m(c)$ to which county c belongs, and year t. Advertising of category k refers to advertising by different sponsors. In the main specification, $K = \{f, s, mp\}$. $ad^{f}_{bm(c)t}$ and $ad^{s}_{bm(c)t}$ denote advertising by federal and state governments, respectively, and $ad^{mp}_{bm(c)t}$ is *market-level* private advertising, defined as the sum of advertising expenditures by all insurers in each DMA and year. In some specifications, we include advertising of other categories to control for additional variables that also vary discretely across DMA borders: insurance navigators (nv) and political advertising on the ACA by Democrats (dem) and Republicans (rep).[24] Note that TV advertising decisions are typically made on

[23]Because a county can have multiple neighboring counties in different DMAs, it can belong to multiple border pairs. To make sure that the regression result is not driven by counties that belong to multiple border pairs, we weight each county by the inverse of the number of border pairs to which it belongs.

[24]The classification of political advertising is based on information on the political party affiliation of advertising sponsors in the data.

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the basis of a DMA, which contains several counties. Thus, we assume individuals in different counties but in the same DMA are exposed to the same advertising level. We add one to the advertising variables before taking the logarithm because there are markets with zero advertising spending by the government or private insurers. Because both dependent and independent variables are in logarithm, coefficients β_{d0} and β_{d1} are elasticities of county-level demand by a demographic group d for marketplace plans with respect to government and private advertising, respectively.

Next, x_{bct} refers to a set of time-varying characteristics for each county-year pair (ct). We include the number of insurers and its quadratic term. To control for unobserved heterogeneity in demand, we include fixed effects for a border pair-by-year (ξ_{bt}), county (ξ_c), and rating area-by-year ($\xi_{r(c)t}$). As discussed above, the border strategy relies on the first two fixed effects. The first controls for time-varying unobserved heterogeneity across border pairs, and the second controls for time-invariant unobservables that vary within border pairs at the county level. In addition, a rating area is a collection of counties within which an insurer sets characteristics for its plans. Thus $\xi_{r(c)t}$ controls for effects of plan characteristics on enrollments, although we do not explicitly include specific plan characteristics in the regression models.

4.1.3 Estimation Results

Table 4 presents regression results from various specifications. Columns (1)--(3) differ only in included fixed effects, and Column (4) controls for additional advertising categories as well as the full set of fixed effects. Standard errors in all specifications are clustered at the level of DMA-by-year because the advertising variables vary at this level.

In all specifications, the coefficient estimates for advertising by the federal government are positive and statistically significant, and their magnitudes are largely invariant across the four specifications. Based on the estimates in Column (3), we find that a 1% increase in federal advertising leads to a 0.045% increase in market shares of individuals that enrolled in the marketplace. Extrapolating the coefficient to larger changes, if the federal government doubles advertising spending, then the market-level share will increase by 4.5%. Given the unconditional average of market-level shares is 0.2, a 4.5% increase is equal to an increase in the market share by 0.9 percentage point. Although the magnitude seems modest, it is still largely consistent with typical findings in the marketing literature estimating elasticity of demand with respect to advertising. For example, Shapiro (2018) estimates advertising elasticity of 0.04 in prescription pharmaceuticals.

In contrast, the coefficient estimates for advertising by state governments are marginally significant only in Column (1), for which we include the smallest set of fixed effects. One

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reason why advertising by state governments is not very effective is because state governments tend to rely more on other consumer assistance programs to provide information for state marketplaces, which may reduce the importance of advertising[25]. Because consumers can learn about marketplaces through other assistance programs, additional information that consumers can obtain solely from advertising might be limited. For the federally facilitated marketplaces, in contrast, advertising may play a more important role because the federal government not provide many other assistance programs.

Next, we find that market-level private advertising is not effective in increasing market-level enrollments. It is marginally significant only in Column (1). This result suggests that private advertising is quite limited in expanding total marketplace enrollments. There are two possibilities that result in this limited effect of private advertising. First, private advertising is not effective for demand for private insurers. Although this possibility raises the question of why a rational insurer would waste resources on advertising, several papers have already found that the effect of advertising on a firm's own demand is quite limited.[26] Second, even if private advertising is effective in increasing demand for insurers that conduct advertising, it does so by stealing consumers from other insurers. In this case, private advertising may just reallocate consumers among insurers and thus have only a limited market-expansion effect. In the next section, we will estimate the effect of advertising on individual insurer demand to further investigate this issue.

In Column (5), we include additional categories of advertising in the regression to control for other factors that also vary discretely across DMA borders: advertising by insurance navigators and political advertising on the ACA by Democrats and Republicans. The coefficient estimates for the three main advertising variables do not vary with the additional variables. Interestingly, the estimated effects of political advertising are consistent with how each party views the ACA. On the one hand, Democratic advertising increases the market-level enrollment, and its effect is comparable to federal advertising. On the other hand, the point estimate for Republican advertising is negative but statistically insignificant.

4.2 Demand Model

We now analyze the impact of advertising on enrollment at the insurer level. This analysis will help us understand whether private insurer advertising is effective in increasing enrollment for the advertising insurer. Moreover, this demand model will be a basis to ex-

[25]State governments often provide in-person assistance or reach out to certain individuals directly. See Lee et al. (2017) and Domurat et al. (2019) for the case of California state marketplace programs.

[26]For example, see Blake et al. (2015), Lewis and Rao (2015), and Sinkinson and Starc (2018).

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Table 4: The Effects of Advertising on Market-level Enrollments

	(1)	(2)	(3)	(4)
Log of Fed Spend	0.051**	0.040***	0.045**	0.045**
	(0.025)	(0.015)	(0.022)	(0.022)
Log of State Spend	0.043*	0.040	-0.026	-0.024
	(0.025)	(0.042)	(0.051)	(0.048)
Log of Priv Spend	0.018*	0.003	0.020	0.022
	(0.011)	(0.011)	(0.015)	(0.014)
Log of Navi Spend				-0.007
				(0.094)
Log of Dem Spend				0.050***
				(0.017)
Log of Rep Spend				-0.010
				(0.008)
No. of Insurers	0.047***	0.007	0.010	0.011
	(0.018)	(0.012)	(0.016)	(0.016)
No. of Insurers $\times$ No. of Insurers	-0.001	0.001	0.001	0.000
	(0.002)	(0.001)	(0.002)	(0.002)
BorderYear FE	Y	Y	Y	Y
County FE		Y	Y	Y
RatingYear FE			Y	Y
N. Obs.	18,862	18,812	18,154	18,154
Adj. R^2	0.778	0.940	0.946	0.947

Note: This table reports the estimates of the coefficients in Equation (2). Different columns have different combinations of Border$\times$Year fixed effects, County fixed effects, and Rating Area$\times$Year fixed effects. Each observation is weighted by by the inverse of the number of border pairs to which it belongs. Standard errors are in parentheses and clustered at the DMA$\times$Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

amine the equilibrium impact of government advertising, which requires an equilibrium model of the health insurance marketplace.

4.2.1 Utility Specification

Consider individual i who lives in market ct, which is based on county-year pair. The number of marketplace insurers available in each market is denoted by J_{ct}. Because the outside option is always available, a consumer has a total of $J_{ct}+1$ options. The consumer optimally chooses the insurer that maximize his utility.[27] We assume that the consumer obtains indirect utility u_{ijct} from insurer $j>0$ as follows:

$$u_{ijct} = \sum_{k\in K} \ln(1+ad^k_{jm(c)t})\beta_k + \xi_{jct} + \epsilon_{ijct} \tag{3}$$

[27] Because plan-level enrollment data are available, it is possible to model plan choice within insurers. However, the data provide the total enrollment for each plan aggregated across multiple counties. Moreover, because the effects of advertising on market- and insurer-level demand are the first order channels, we leave this extension for future work.

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An individual's insurer choice is affected by the amount of advertising in various categories $ad^k_{jm(c)t}$, where each category is defined over advertisement sponsor and content. It is also affected by non-advertising utility from an insurer (ξ_{jct}).[28] The set of advertising categories we consider in the main specification is a collection of the per-capita spending by different advertising sponsors: $K = \{f, s, p, r\}$, each element of which is defined as follows. As in the market-level analysis, $ad^f_{jm(c)t}$ and $ad^s_{jm(c)t}$ denote advertising by the federal government and state governments, respectively. Although these two variables have the j subscript, they do not change across insurers within the same DMA and year. Thus, if advertising by governments increases an insurer's market shares, it will increase all other insurers' market shares in the same way, thereby expanding the total enrollment in marketplace plans. We relax this assumption in Section 4.3.4.

We let $ad^p_{jm(c)t}$ denote advertising by insurer j, which varies over insurers within the same market. An important difference from the market-level analysis is that we consider $ad^p_{jm(c)t}$ instead of market-level private advertising ($ad^{mp}_{m(c)t}$). Note that with our framework, an insurer j's advertising will inherently have business-stealing effects. In other words, its advertising will increase its own market share at the expense of rivals' market shares. Thus, the effect on the total enrollment can be limited even if private advertising is as effective as government advertising in increasing demand for an individual insurer. To allow for a more flexible substitution pattern among insurers with respect to private advertising, we include advertising by an insurer's rivals (r) in some specifications such that $ad^r_{jm(c)t} = \sum_{h \neq j} ad^p_{hm(c)t}$.[29] The coefficient for $ad^r_{jm(c)t}$ will determine whether private advertising just steals business from rivals or has positive spillover to rivals. To the extent that some private advertising provides specific information about the marketplace–for example, the open enrollment period, it could potentially have positive spillover to rivals. On the one hand, if the coefficient is positive and large enough, then private advertising can increase not only the insurer's own demand but also rivals' demand, thereby leading to market expansion. On the other hand, if the coefficient is positive but not large enough or even negative, private advertising will have a business-stealing effect.

Lastly, we include additional categories in K in some specifications to control for other variables that also discretely vary at DMA borders. As in the market-level regression, we consider advertising by insurance navigators ($ad^{nv}_{jm(c)t}$) and political advertising by

[28]We assume 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 the 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.

[29]We also experimented with an alternative specification, where we define rivals' advertising as the average per-capita spending by rivals. This variable definition does not affect our results.

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Democrats ($ad^{dem}_{jm(c)t}$) and Republicans ($ad^{rep}_{jm(c)t}$). Note that advertising of these categories does not vary across insurers within a DMA in each year.

The non-advertising utility (ξ_{jct}) denotes utility from characteristics of an insurer's plans such as premiums, generosity of coverage, provider networks, and so on. It also includes an insurer's characteristics such as brand image. For the purpose of this paper, it is not very crucial to estimate how much utility depends on specific plan characteristics. Thus, we do not explicitly model how each plan characteristic affects utility.

A consumer's outside option $(j = 0)$ is to stay as uninsured, from which a consumer receives utility of u_{i0ct}:

$$u_{i0ct} = \epsilon_{i0ct}. \tag{4}$$

Note that δ_{0ct} is normalized to 0 for all ct because only the relative utilities can be identified in a discrete choice model. Lastly, ϵ_{ijct} is an individual i's preference shock for each plan. We assume that ϵ_{ijct} is independently and identically distributed according to a Type I extreme-value distribution.

Also, note that variables in the utility function do not include the subscript for border pair (b) because we will first write a general model for demand for insurers for now. When we estimate the model, we will also employ the border strategy, where we will add the subscript for border areas (b) to appropriate variables when discussing identification.

4.2.2 Identification and Estimation

To estimate the model, we exploit the one-to-one mapping between each insurer's market share and the deterministic part of u_{ijlct} given in Equation (3) as in Berry (1994). Define $\delta_{jct} \equiv u_{ijct} - \epsilon_{ijct}$. Then it is easy to show, based on the assumption on ϵ_{ijct}, that

$$\delta_{jct} = \ln(s_{jct}) - \ln(s_{0ct}),$$

where s_{jct} denotes insurer $j's$ empirical market share. We will denote the empirical counterpart of δ_{jct} by $\hat{\delta}_{jct}$. Then the estimating equation is given by:

$$\hat{\delta}_{jct} = \sum_{k \in K} \ln(1 + ad^{k}_{jm(c)t})\beta_k + \xi_{jct}. \tag{5}$$

Notice that estimating coefficients in Equation (5) simply requires running a linear regression. However, estimating the coefficients with an ordinary least square regression is likely to result in biases in our advertising coefficients (β_k) because of endogeneity of advertising, which was discussed earlier in Section 4.1.1. Thus, we employ the border

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strategy to estimate the coefficients.

Border Strategy at the Insurer Level Consider an insurer j in county c in border pair b. With the border strategy, we assume that the insurer's non-advertising utility is

$$\xi_{jbct} = \xi_{jbt} + \xi_{jr(c)t} + \xi_c + \Delta\xi_{jbct}. \tag{6}$$

First, ξ_{jbct} refers to fixed effects for insurer j, border pair b, and year t. They capture any common factor that affects demand for insurer j in both counties in border pair b in year t. Second, $\xi_{jr(c)t}$ denotes fixed effects for insurer j, rating area $r(c)$, and year t. An insurer is restricted to offer the same price for a given plan within a rating area and a year. Thus, we indirectly control for an insurer's plan characteristics with $\xi_{jr(c)t}$. Third, ξ_c refers to county fixed effects, which capture any time-invariant factor that commonly affects demand for insurers in a county. Lastly, $\Delta\xi_{jbct}$ denotes the remaining component in ξ_{jbct}.

Combining Equations (5) and (6), we have the following estimating equation with the border strategy.

$$\hat{\delta}_{jbct} = \sum_{k\in K} \ln(1 + ad^k_{jbm(c)t})\beta_k + \xi_{jbt} + \xi_{jr(c)t} + \xi_c + \Delta\xi_{jbct} \tag{7}$$

The identifying assumption is that none of the advertising variables are correlated with the structural error term $\Delta\xi_{jbct}$–i.e., unobserved heterogeneity in demand for an insurer that varies at the level of county and year within a border pair.[30]

4.2.3 Estimation Results

Table 5 presents coefficient estimates in the utility function described in Equation (3) with different specifications. Columns (1)--(5) differ only in the included fixed effects and advertising controls. Standard errors for all specifications are clustered at the level of DMA-by-year because main advertising variables vary at this level.

Table 5 shows that, in all specifications, an insurer's own private advertising is effective in increasing demand for an insurer. Based on the estimate from Column (3), which contains the most extensive set of fixed effects, the average elasticity of insurers demand

[30]Because a county can have multiple neighboring counties in different DMAs, it can belong to multiple border pairs. To make sure that the regression result is not driven by insurers in counties that belong to multiple border pairs, we weight each insurer×county by the inverse of the number of border pairs to which it belongs.

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with respect to advertising is 0.04 among insurers that had positive advertising spending.[31] The magnitude of this estimated impact of *private advertising* is largely consistent with typical findings in the marketing literature estimating the elasticity of demand with respect to advertising (see Shapiro et al. (2019)).

We also find that the estimate for rivals' advertising (Columns (4) and (5)) is not statistically significant. This suggests that private advertising does not have positive spillover to rivals and that it merely has a business-stealing effect. This finding is consistent with the finding from the county-level regression in Section 4.1.3 that market-level aggregate private advertising has limited market-expansion effects. If demand for an insurer increases at the expense of its rivals, private advertising may very limited effects on increasing the market-level enrollment.

The estimates for advertising by federal and state governments are consistent with our finding with the market-level regression. Federal advertising is effective in increasing demands for all insurers, whereas advertising by state governments has limited effects. The estimates from this model of demand provide evidence that private advertising has a very different effect on enrollment than does advertising by the federal government. While federal advertising increases market-level enrollments, advertising by a private insurer only reallocates demand to its products away from its competitors, with little net effect on overall enrollment.

Effects of Advertising in New vs. Mature Markets A natural question is whether the effectiveness of advertising varies with the length of time the marketplace has been active. If the main channel through which government advertising increases enrollment is through information provision, then advertising might be the most effective during the early years of the marketplace, when many potential buyers are uninformed about features of the marketplace necessary for enrollment (such as the open enrollment period). If this is the case, then the government might want to spend advertising resources in the early years, when potential buyers are new to the marketplace.

Similar reasoning might motivate the government to reduce advertising as the marketplace becomes more mature. Once consumers enroll, they are likely to be informed about the process. Further, they may simply re-enroll in the same plan every year, not requiring advertising to induce re-enrollment. However, if there is a steady influx of new customers to the marketplace each year, then advertising may still be effective, even when the marketplace is mature. How the government should allocate advertisement spending

[31]Because the elasticity becomes zero for insurers with zero advertising spending, we only calculated the number among insurers with positive advertising.

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Table 5: Estimated Coefficients in Insurer-Level Demand Model

	(1)	(2)	(3)	(4)	(5)
Log of Fed Spend	0.023	0.084*	0.115**	0.117**	0.120**
	(0.050)	(0.045)	(0.051)	(0.051)	(0.051)
Log of State Spend	0.161**	0.046	-0.024	-0.014	-0.012
	(0.065)	(0.086)	(0.071)	(0.072)	(0.073)
Log of Priv Spend	0.209***	0.270***	0.124***	0.106***	0.104***
	(0.032)	(0.045)	(0.039)	(0.040)	(0.040)
Log of Rival Spend				-0.037	-0.040
				(0.038)	(0.038)
Log of Navi Spend					-0.004
					(0.173)
Log of Dem Spend					0.046
					(0.032)
Log of Rep Spend					0.011
					(0.015)
No. of Insurers	-0.375***	-0.401***	-0.383***	-0.379***	-0.375***
	(0.038)	(0.042)	(0.050)	(0.051)	(0.051)
No. of Insurers × No. of Insurers	0.020***	0.026***	0.026***	0.026***	0.025***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
FirmBorderYear FE	Y	Y	Y	Y	Y
County FE		Y	Y	Y	Y
FirmRatingYear FE			Y	Y	Y
N. Obs.	39,758	39,726	38,272	38,272	38,272
Adj. R^2	0.833	0.866	0.929	0.929	0.930

Note: This table reports the estimates of the coefficients in Equation (7). Different columns have different combinations of Firm×Border×Year fixed effects, County fixed effects, and Firm×Rating Area×Year fixed effects. Columns (4) and (5) present the estimates with specifications with additional advertising variables. Each observation is weighted by the inverse of the number of border pairs to which it belongs. Standard errors are in parentheses and clustered at the DMA×Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

across the life-cycle of the marketplace depends on the effectiveness of advertising across time.

We examine whether the effect of advertising has decreased over time. We compare the estimates in Table 4, which are based on data up to 2018, with estimates obtained with subsamples up to 2016 and 2017, separately.[32] Although this comparison is based on relatively small differences in time, if advertising is more effective in the early years of the health insurance marketplace, we should expect that our estimates will decrease over years.

Table 6 presents results from this exercise and suggests that the effectiveness of government advertising has indeed decreased over time. However, we still find non-trivial effects even with the full sample (Column (3)). A more precise answer to the question of changes in effectiveness across time requires a longer time horizon, but the evidence sug-

[32]We do not consider the subsample up to 2015 because we need to enough time variation in advertising within a county to estimate the impact of advertising. Moreover, relevant regulations (e.g., the individual mandate) were not fully effective until 2016.

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Table 6: The Effects of Advertising: New vs Mature Markets

	(1) Up to 2016	(2) Up to 2017	(3) Up to 2018
Log of Fed Spend	0.132**	0.124**	0.115**
	(0.056)	(0.052)	(0.051)
Log of State Spend	0.032	0.070	-0.024
	(0.085)	(0.073)	(0.071)
Log of Priv Spend	0.096**	0.124***	0.124***
	(0.041)	(0.041)	(0.039)
No. of Insurers	-0.254***	-0.382***	-0.383***
	(0.058)	(0.057)	(0.050)
No. of Insurers $\times$ No. of Insurers	0.011**	0.025***	0.026***
	(0.005)	(0.006)	(0.005)
FirmBorderYear FE	Y	Y	Y
County FE	Y	Y	Y
FirmRatingYear FE	Y	Y	Y
N. Obs.	26,754	32,946	38,272
Adj. R^2	0.932	0.929	0.929

Note: This table reports the estimates of the coefficients in Equation (7). Columns (1)–(3) present the estimates with the sample period up to 2016, 2017, and 2018, respectively. All specifications include Firm$\times$Border$\times$Year fixed effects, County fixed effects, and Firm$\times$Rating Area$\times$Year fixed effects. Each observation is weighted by the inverse of the number of border pairs to which it belongs. Standard errors are in parentheses and clustered at the DMA$\times$Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

gests that advertising is particularly important in the early years of the marketplace. This lends some credibility to the view that an important channel for government advertising is information provision.

4.3 Additional Results

The results above show that advertising by the federal government and private insurers are effective in increasing market- or insurer-level enrollments. Here, we examine heterogeneous effects of advertising. First, we investigate whether advertising with certain content is more effective. Second, we investigate if advertising is more effective for certain consumers or markets. Third, we investigate whether private advertising is more effective depending on government advertising.

4.3.1 Content in Advertisements

To explore whether certain advertising content is more effective, we group advertisements into different categories depending on which information they provide. Then we calculate expenditures for each category and estimate how effective each category is. We

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consider the following two most common categories of information provided in advertisements: financial assistance and the open enrollment period.

We estimate the impact of each advertising content separately. For financial assistance, we define $ad^{k_{FA1}}_{jm(c)t}$ to be advertising expenditures per potential enrollee of category k providing information on financial assistance. We also define $ad^{k_{FA0}}_{jm(c)t} \equiv ad^{k}_{jm(c)t} - ad^{k_{FA1}}_{jm(c)t}$. In other words, it denotes advertising expenditures per potential enrollee of category k not providing information on financial assistance. Then we estimate the regression described by Equation (7) with $K = \{f_{FA1}, f_{FA0}, s_{FA1}, s_{FA0}, p_{FA1}, p_{FA0}\}$. For the open enrollment period, we also define advertising variables in a similar way ($ad^{k_{OP1}}_{jm(c)t}$ and $ad^{k_{OP1}}_{jm(c)t}$) and estimate Equation (7) with $K = \{f_{OP1}, f_{OP0}, s_{OP1}, s_{OP0}, p_{OP1}, p_{OP0}\}$.

Table 7 shows coefficient estimates with subsamples containing data up to different years. First, we find that federal advertising providing information about financial assistance is more effective than other categories of federal advertising with the subsample up to 2016 (Column (1)). The magnitude is much larger than the coefficient for federal advertising in the baseline specification (β_f in Equation 3). However, the magnitudes are lower with the subsamples up to 2017 and 2018. Although it is much larger than the estimate in the baseline specification, it is not statistically significant in Column (2) or (3) because of larger standard errors. The estimates for federal advertising providing information about the open enrollment period exhibit a similar pattern: the largest in Column (4) and smaller in Columns (5) and (6).

These patterns are consistent with our result with respect to new vs mature markets (Table 6). The specific information provided by federal advertising is likely the most valuable in the early years of the marketplace. As the market becomes more mature, consumers are increasingly more likely to already be aware of such information. In contrast, the same categories of advertising by private insurers are not nearly as effective as federal advertising. None of the estimates for either category is statistically significant in any subsamples, and their magnitudes are typically much lower than the coefficient estimate for private advertising in the baseline specification (β_p in Equation 3). This result suggests that private insurers are not effective in increasing enrollments with informative advertising, and it is consistent with our earlier finding that private advertising has limited effects on market-level enrollments. If private advertising was very effective in providing general information about the marketplace, we would expect that it would have positive spillovers to rivals' enrollments and have greater impacts on market-level enrollments.[33] Moreover, the fact that the effectiveness of private advertising did not decrease over time

[33]For example, Shapiro (2018) and Sinkinson and Starc (2018) find spillovers of advertising in the context of prescription drugs.

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as shown in Table 6 also suggests that information provision regarding the marketplace is not the main channel through which private advertising affects enrollment.

Table 7: Coefficient Estimates for Advertising Contents

	Content = Financial Assistance			Content = Open Enrollment		
	(1) Up to 2016	(2) Up to 2017	(3) Up to 2018	(4) Up to 2016	(5) Up to 2017	(6) Up to 2018
Log of Fed Spend (Content)	0.509**	0.302	0.259	0.502*	0.348*	0.325*
	(0.248)	(0.188)	(0.177)	(0.275)	(0.199)	(0.188)
Log of Fed Spend (rest)	0.047	0.064	0.063	0.073	0.069	0.061
	(0.048)	(0.048)	(0.049)	(0.048)	(0.047)	(0.049)
Log of State Spend (Content)	0.114	0.121	0.174	-0.102	0.016	0.083
	(0.088)	(0.113)	(0.112)	(0.237)	(0.124)	(0.102)
Log of State Spend (rest)	0.024	0.059	-0.072	0.098	0.116	-0.040
	(0.101)	(0.078)	(0.082)	(0.100)	(0.093)	(0.087)
Log of Priv Spend (Content)	0.082	0.033	0.021	0.062	0.008	0.002
	(0.062)	(0.056)	(0.051)	(0.068)	(0.061)	(0.055)
Log of Priv Spend (rest)	0.093*	0.146***	0.150***	0.106*	0.166***	0.168***
	(0.054)	(0.052)	(0.049)	(0.059)	(0.056)	(0.052)
No. of Insurers	-0.250***	-0.379***	-0.381***	-0.254***	-0.380***	-0.382***
	(0.058)	(0.057)	(0.051)	(0.057)	(0.057)	(0.050)
No. of Insurers × No. of Insurers	0.011**	0.025***	0.026***	0.011**	0.025***	0.026***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
BorderYear FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
RatingYear FE	Y	Y	Y	Y	Y	Y
N. Obs.	26,754	32,946	38,272	26,754	32,946	38,272
Adj. R^2	0.932	0.929	0.930	0.932	0.929	0.930

Note: This table reports the estimates of the coefficients in Equation (7). For Columns (1)–(3), the set of categories of advertisements we consider is $K = \{f_{FA1}, f_{FA0}, s_{FA1}, s_{FA0}, p_{FA1}, p_{FA0}\}$. For Columnn (4)–(6), the set of categories of advertisements we consider is $K = \{f_{OP1}, f_{OP0}, s_{OP1}, s_{OP0}, p_{OP1}, p_{OP0}\}$. All specifications include Firm×Border×Year fixed effects, County fixed effects, and Firm×Rating Area×Year fixed effects. Each observation is weighted by the inverse of the number of border pairs to which it belongs. Standard errors are in parentheses and clustered at the DMA×Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

4.3.2 Heterogeneous Effects across Markets

We now investigate whether the effect of advertising varies with market characteristics. We first examine whether the effect depends on the share of unhealthy individuals in a market, using a county's share of individuals self-reporting poor or fair health as a measure of county-level health status. We define an "unhealthy" market as a market in the top quartile of self-reported poor or fair health. This includes all markets with greater than 21% individuals reporting fair or poor health. Then we interact the health variable with advertising categories with statistically significant effects: federal and private advertising.

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Columns (1) in Table 8 presents the coefficient estimates. Both of the interaction terms with federal and private advertising are negative and statistically significant. Note that the total effects of both federal and private advertising for unhealthy markets are close to zero and statistically insignificant.[34] In sum, there is a large degree of heterogeneity in the effects of federal and private advertising. Their effects are positive only in markets with smaller shares of unhealthy individuals.

This result is in general consistent with the view that advertising may work as a form of risk selection by enrolling more healthy individuals (Aizawa and Kim (2018)). Although we find that neither private nor federal advertising is targeted to healthier markets in Section 3.3, federal and private advertising still induces healthier individuals to enroll disproportionately more in the marketplace. Given the lack of individual-level data on health status and enrollment, however, we cannot rule out the possibility that the market-level health measure is correlated with other differences across markets such as demographic composition. At least, we find only a modest level of heterogeneity in the effect of advertising across demographic types, as will be discussed in Section 4.3.3.

Next, we investigate whether the effect of advertising depends on whether a state expanded Medicaid (Column (2) in Table 8). We find that none of the coefficients for the interaction terms between advertising and the Medicaid expansion status is statistically significant. Thus, although more private advertising is targeted to markets in states that expanded Medicaid, it is not necessarily more effective.[35]

4.3.3 Age and Income

In our main specification, we do not allow effects to vary with consumer demographics. To examine if certain consumers are more responsive to advertising, we examine whether the effect of advertising depends on different age and income groups. Specifically, we estimate Equation (7) for each age and income group. In these regressions, we exclude California and New York from the sample because we do not have data on enrollments by demographic groups in the two states. The main results are reported in Table 15 in

[34] P-values for the total effects of federal and private advertising for unhealthy markets are 0.51 and 0.87, respectively.

[35] A caveat in interpreting this result is that there can be other factors that also affect the effectiveness of advertising between states with and without Medicaid expansion. Moreover, even without the other factors, Medicaid expansion does not necessarily mean that advertising becomes more effective although it could make the risk pool in the marketplace healthier and increase an insurer's per-enrollee profitability. Aizawa and Kim (2018) find that healthy individuals are more responsive to advertising in general but that not every dimension of health characteristics is relevant for advertising. Thus, the effectiveness of advertising will depend on whether individuals with certain health characteristics that matter for advertising are more or less likely to enroll in Medicaid.

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Table 8: Heterogeneous Effects Depending on Market-level Health Status

	(1) Market Characteristics = Unhealthy Market	(2) Market Characteristics = Medicaid Expansion
Log of Fed Spend	0.142**	0.025
	(0.055)	(0.065)
Market Characteristic=1 × Log of Fed Spend	-0.188**	0.153
	(0.078)	(0.100)
Log of State Spend	-0.016	-0.014
	(0.068)	(0.070)
Log of Priv Spend	0.166***	0.193***
	(0.044)	(0.067)
Market Characteristic=1 × Log of Priv Spend	-0.157***	-0.095
	(0.059)	(0.081)
No. of Insurers	-0.385***	-0.382***
	(0.051)	(0.050)
No. of Insurers × No. of Insurers	0.026***	0.026***
	(0.005)	(0.005)
FirmBorderYear FE	Y	Y
County FE	Y	Y
FirmRatingYear FE	Y	Y
N. Obs.	38,272	38,272
Adj. R^2	0.930	0.930

Note: This table reports the estimates of the coefficients in Equation (7). Column (1) reports the result that includes interaction terms between advertising variables (federal and private) and a dummy variable for "unhealthy" markets. A market is defined as unhealthy if the share of individuals with fair or poor self-reported health status in the market is greater than the 75th percentile (21%). Column (2) reports the result that includes interaction terms between advertising variables (federal and private) and a dummy variable for Medicaid expansion status under the ACA. The specifications include Firm×Border×Year fixed effects, County fixed effects, and Firm×Rating Area×Year fixed effects. Each observation is weighted by the inverse of the number of border pairs to which it belongs. Standard errors are in parentheses and clustered at the DMA×Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

the Online Appendix. We find modest heterogeneity in advertising impacts across demographic groups. For example, we find that federal advertising is much more effective for individuals aged 35 or older, while private advertising is almost equally effective for all age groups. With respect to income groups, we find that advertising is more effective for individuals with lower incomes. These consumers face lower net premiums because premium subsidies are larger for them in general (see Section 2), and this could be why they are more responsive to advertising.

4.3.4 Interaction between Government and Private Advertising

The previous specifications assume that there is no complementarity between government and private advertising in terms of their effects on demand. We conducted an additional analysis by adding interaction terms between government and private advertising in the demand model. In Table 16 in the Online Appendix, we show that these interac-

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tion terms are statistically insignificant and close to zero at the point estimates especially for federal advertising. This suggests that the effect of private advertising does not vary depending on the amount of federal advertising in the same market.

5 Counterfactual Experiments

In order to analyze various design questions of government marketing activities, it is crucial to account for an endogenous response of private insurers. Here we discuss the supply side of our equilibrium model and estimation strategy. Then, we describe how to conduct counterfactual experiments.

5.1 Supply-Side Model of Advertising in Health Insurance Marketplaces

In the model, we assume that each insurer j chooses advertising ad^p_{jmt} in DMA-year mt. To simplify the analysis, we take insurance companies' geography choices and product characteristics, including pricing, as exogenous in these counterfactuals. Let π_{jmt} be the average flow profit of insurer j by enrolling an individual in a DMA market m in year t, net of claim costs to insure this consumer, without considering the cost of advertising. Then, an insurer's annual profit at DMA market is expressed as:

$$\Pi_{jmt} = \pi_{jmt} q_{mt}(ad^f_{mt}, ad^s_{mt}, \boldsymbol{ad^p_{mt}}) - C_{jmt}(ad^p_{jmt}), \tag{8}$$

where q_{jmt} is the DMA-level consumer demand of insurer j given the advertising by the federal government (ad^f_{mt}), state governments (ad^s_{mt}), and each private insurer ($\boldsymbol{ad^p_{mt}}$), and $C(\cdot)$ is the cost of advertising by insurer j (ad^p_{jmt}). We use the demand model given by Equation (3) and the coefficient estimates given by Column (3) in Table 5. Note that π_{jmt} captures not only the premium revenue and expected reimbursement costs for this enrollee but also other relevant ACA policies such as risk adjustment. Instead of fully specifying different components that determine profitability, we focus on endogenous responses by insurers through advertising in our counterfactual analysis. Moreover, we also make several simplifying assumptions. First, private insurers only choose total advertising spending at each DMA market, abstracting from content choices. Second, we abstract from potential heterogeneity in profits from consumers with different characteristics. Although it is certainly possible to relax both assumptions, the main economic mechanisms that we highlight in this analysis will remain the same even in such an extended environment.

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In this model, government advertising can alter an insurer's incentive for advertising because both types of advertising can affect demand for an insurer. In addition, there are possible strategic interactions among insurers because demand for an insurer depends not only on its own advertising, but also on other insurers' advertising.

We assume that each insurer chooses its own advertising to maximize the total profits Π_{jmt} in each DMA-year market, mt.[36] In the static Bertrand-Nash equilibrium, the interior equilibrium advertising expenditure is the solution to the first-order condition:

$$\frac{\partial \Pi_{jmt}}{\partial ad^{p}_{jmt}} = 0. \tag{9}$$

We use this equilibrium condition in our counterfactual analysis. We also utilize Equation (9) to estimate the average annual flow profit per enrollee π_{jmt}. The main idea is that the first order condition will allow us to express π_{jmt} as a function of the derivative of insurer-level enrollment with respect to advertising ad^{p}_{jmt} evaluated at the observed level. We can calculate the derivative using our estimates of the consumer demand model. One important caveat is that this equilibrium condition does not necessarily hold especially for insurers with zero equilibrium advertising. To keep our analysis simple, our counterfactual analysis considers re-optimization by insurers with positive baseline advertising expenditures.[37] The detail of estimation procedure is described in Appendix B.

We find that the median estimated π_{jmt} among insurers with positive advertising is about \$565. We view this magnitude as reasonable. The average annual benchmark premium in the marketplace in 2017 is about \$4,320 according to the Kaiser Family Foundation.[38] If insurers expect to have 10% to 15% profit margin, especially given an 80% medical loss ratio requirement under the ACA, our estimated perceived profitability of \$565 is reasonable.

5.2 Implication of Changing Government Advertising

We use the estimated equilibrium model to examine the importance of government advertising by exogenously changing its level. Based on demand estimate that state advertising is not statistically significant, we only consider changing federal advertising. We first simulate market outcomes in a scenario where private insurers do not respond to the

[36]This is a limited approach because insurers may decide how much to advertise to maximize their long-run profits. Fully characterizing the dynamic problem is a very challenging task; therefore, we plan to approach it after obtaining main results under the static decision problem.

[37]Our main economic channels in the counterfactual analysis are likely to remain the same even if we allow all insurers to re-optimize their advertising.

[38]https://www.kff.org/health-reform/state-indicator/average-marketplace-premiums-by-metal-tier

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change. Then we calculate market outcomes by solving for an equilibrium in which private insurers optimally adjust their advertising spending. Because there was no federal advertising in 2018, we focus on markets with positive federal government advertising in 2014-2017.

Table 9: Counterfactual Experiments: Changes in Federal Government Advertising Spending

		Benchmark	Fed Ad×0		Fed Ad×3	
			Partial eq.	Full eq.	Partial eq.	Full eq.
All Markets	Enrollment (%)	18.98	18.61	18.63	19.50	19.48
	Private Advertising ($)	1.43	1.43	1.51	1.43	1.35
Market with Large Federal Ad Spending (top 10%)	Enrollment (%)	17.87	16.68	16.75	19.03	18.97
	Private Advertising ($)	1.65	1.65	2.10	1.65	1.41

Note: This table presents simulated outcomes in counterfactual scenarios. Column "Benchmark" presents outcomes observed in the data. Column "Fed Ad×0" presents outcomes in a scenario where federal advertising is shut down to zero. Column "Fed Ad×3" presents outcomes in a scenario where federal advertising is tripled. "Partial eq." present outcomes, assuming private insurers do not adjust their advertising. "Full eq." present outcomes, allowing for private insurers to re-optimize their advertising. We report outcomes for all markets and only for markets with large federal advertising spending. The latter is defined as markets with top 10% of federal advertising spending in the benchmark. The reported numbers are averages of DMA×Year-level enrollments and total private advertising spending per capita. In the benchmark economy, the average federal advertising is $0.32 per capita for all markets and $1.26 per capita for markets with large federal spending.

Table 9 shows the main results. First, we find that reducing federal government spending to zero modestly reduces the market-level enrollment. Although the overall effect is small (18.98% to 18.63%), market-level effects depend on the baseline government spending. For markets with larger baseline government spending (top 10% or above $0.68 per capita)[39], we find that the decline in enrollment is about 1.12 percentage points. Importantly, equilibrium responses of private insurers have little effect on market-level enrollment. This finding is important because we find that private insurers indeed increase their advertising substantially in response to the counterfactual change in federal advertising. On average, a dollar decrease in federal advertising spending per capita increases private advertising by $0.25.[40] In markets with large baseline government spending, we find that private advertising increases by $0.45 per capita, which is equivalent to a $0.36 increase for a dollar decrease in federal advertising.[41] The finding

[39]The average baseline government spending is $0.32 per capita for all markets and $1.26 per capita for markets with large federal advertising spending.

[40]This number is obtained by dividing the change in private advertising (0.08) by the baseline federal advertisement spending (0.32).

[41]This result may also be affected by the specification of the demand model, where we do not include

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that market-level enrollment changes little suggests that private advertising has very limited market-expansion effects. Note that our estimates in the consumer demand model show private advertising is effective in increasing an insurer's own demand. Thus, our finding suggests that private advertising is driven by rent-seeking competition among insurers, which may lead to a waste of resources. This differs from federal advertising, which affects all the insurers more or less evenly (see Section 4.3.4). Moreover, this finding also indicates that government and private advertising are substitutes in the sense that a reduction in government advertising increases private advertising. However, the substitution between federal and private advertising has very different implications on marketplace enrollment.[42]

Table 9 also reports results from another counterfactual experiment, where government advertising is increased by three times. We find that market enrollment increases, close to a 6% increase from the baseline economy (or an 1.10 percentage points increase) in markets with large baseline federal advertisement spending. Consistent with results from the scenario where we shut down government advertising, this additional government advertising lowers private advertising. However, a comparison between "Partial eq." and "Full eq." shows that the overall market-level enrollment will remain the same despite the decrease in private advertising. This finding suggests that government advertising is beneficial not only to increase enrollment, but also to mitigate possibly excessive advertising competition among private insurers with a decrease in private advertising by $0.13 for a dollar increase in government advertising.

Of course, it is important to note that this does not necessarily mean that all of private advertising is just waste of resources. It is possible that, by inducing consumers to switch to better insurers, it could improve consumer welfare if insurers spending more on advertising tend to provide better plans. Although it is difficult to quantify this wel-

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the interaction between private and government advertising as a determinant of consumer demand. As discussed in Section 4.3.4, we do not find a statistically significant estimate for the interaction term between the two advertising variables.

[42]One might think that we could further validate our model externally by comparing our counterfactual results and empirical estimates of changes in private advertising in response to the cut of federal advertising in 2018. Because federal advertising was distributed unevenly across regions, one can potentially estimate the response by private insurers with a difference-in-differences (DID) regression. We explored the possibility but found that the common trend assumption in DID is unlikely to be met. Comparing neighboring DMAs with larger and smaller pre-2018 federal advertisement spending, we found that pre-2018 private advertisement spending did not change similarly over years between the two types of DMAs. This may be because the marketplace was still evolving differently across markets in its first few years. When we estimated the DID regression despite the likely violation of its identifying assumption, we found that the point estimates of the impact of the 2018 cut in federal advertising on private advertising tend to be positive–which is consistent with our counterfactual results–but are statistically insignificant due to large standard errors. Given the difficulty of applying the DID research design, we do not rely on the DID estimates to validate the counterfactual results.

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fare effect due to the multi-dimensional characteristics of health insurance contracts[43], it is reasonable to expect that welfare gains from switching to better insurers are much smaller than welfare gains from enrolling previously uninsured individuals in any insurance plan. This is in part because the marketplace regulates minimum quality of health insurance plans, which is set as 60% of actuarial fair value. Consistent with this view, Finkelstein et al. (2019) estimate that willingness to pay for switching to a more generous plan is just 11-30% of willingness to pay from switching from being uninsured to being insured with a less generous plan in the Massachusetts marketplace. Although a more complete welfare analysis is left for future work[44], our finding suggests that marketing campaigns by the government are beneficial and an effective tool to mitigate consumer frictions in newly created private markets and to reduce rent-seeking advertising competition among private insurers.

5.3 Welfare Implication of Targeting of Federal Advertising

Finally, we use our model to investigate the extent to which the objectives of the federal government and private insurers differ. We do not consider state advertising by state governments because we did not find it very effective in increasing enrollments. We first specify the government objective function as follows:

$$\max_{ad^f_{mt}} W_{mt} q_{mt}(ad^f_{mt}, ad^s_{mt}, \boldsymbol{ad^p_{mt}}) - C(ad^f_{mt}),$$

where W_{mt} is the federal government's perceived social welfare from enrolling a consumer in DMA m in year t. This specification is similar to the specification of a private insurer's profit function. An important difference is W_{mt} and π_{jmt}. We assume that the parameter W_{mt} captures a weighted average of consumer and producer surplus, government expenditures on subsidies, and redistributional preferences held by the government. We can back out this parameter using the same approach to recover an insurer primitive π_{jmt}. We use this parameter to shed further light on how government targeting differs from private targeting.

We find that the median estimate of W_{mt} is about \$75. Although the magnitude is much smaller than our estimates of an insurer's profitability, it looks very reasonable if we take into account sizable government spending on premium subsidies. Importantly,

[43]Grossman and Shapiro (1984) offers a theoretical analysis that shows that the welfare impacts of advertising in an economy with differentiated products are highly non-trivial.

[44]We did not attempt to conduct a complete welfare analysis because it would require us to specify how advertising affects demand.

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although W_{mt} and π_{jmt} are positively correlated, the magnitude of their correlation coefficient (about 0.10) is not very large. This number indicates that there is a large degree of disagreement between the federal government and private insurers in their objective functions. Thus, it is likely difficult for private markets alone to generate a welfare-maximizing level of advertising from the government's perspective. Assuming that the government's utility is closer to the social planner's utility, we view this finding as additional evidence that government marketing activities are more socially desirable.

6 Conclusion

This paper studies government advertising in publicly designed private markets in the context of health insurance marketplaces. We first show suggestive evidence that advertisements by the government (both federal and states) and private insurers are targeted to different geographical area and provide different messaging contents. Then, we estimate the impact of government and private advertising on marketplace enrollment. Our empirical design exploits discontinuities in advertising along the borders of local TV advertising markets to address the endogeneity of advertising. We find that government advertising has a market-expansion effect, while private advertising tends to steal consumers from other insurers. These findings suggest that government advertising may play an important role by reducing possible information frictions that consumers face to sign up for health insurance plans. Finally, we estimate an equilibrium model of the health insurance marketplace to examine the impact of changing government advertising spending. We find that government advertising increases total program enrollment and reduces inefficient rent-seeking advertising competition among private insurers, suggesting welfare benefit of government advertising as a market design tool.

We view this study as a first step towards understanding government marketing and outreach activities for publicly designed private markets. Future work should explore the role of government advertising in other markets, such as those for education and mortgages. Another interesting avenue to explore is the effectiveness and efficiency of other marketing and outreach activities beyond TV advertising.

References

Aizawa, N. and Y. S. Kim (2018). Advertising and risk selection in health insurance markets. *American Economic Review 108*(3), 828–67.

Aizer, A. (2007). Public health insurance, program take-up, and child health. *The Review of Economics and Statistics 89*(3), 400–415.

Electronic copy available at: https://ssrn.com/abstract=3434450

Allende, C., F. Gallego, and C. Neilson (2019). Approximating the equilibrium effects of informed school choice. Working Paper, Princeton University.

Andrabi, T., J. Das, and A. I. Khwaja (2017). Report cards: The impact of providing school and child test scores on educational markets. *American Economic Review 107*(6), 1535–63.

Barry, C., S. Bandara, K. Arnold, J. Pintor, L. Baum, J. Niederdeppe, P. Karaca-Mandic, E. Fowler, and S. Gollust (2018). Assessing the content of television health insurance advertising during three open enrollment periods of the aca. *Journal of Health Politics, Policy and Law 43*(6), 961–989.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Bertrand, M., D. Karlan, S. Mullainathan, E. Shafir, and J. Zinman (2010). What's Advertising Content Worth? Evidence from a Consumer Credit Marketing Field Experiment*. *The Quarterly Journal of Economics 125*(1), 263–306.

Bhargava, S., G. Loewenstein, and J. Sydnor (2017). Choose to Lose: Health Plan Choices from a Menu with Dominated Option. *The Quarterly Journal of Economics 132*(3), 1319–1372.

Black, S. E. (1999). Do better schools matter? parental valuation of elementary education*. *The Quarterly Journal of Economics 114*(2), 577–599.

Blake, T., C. Nosko, and S. Tadelis (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica 83*(1), 155–174.

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

Cabral, M., M. Geruso, and N. Mahoney (2018). Do larger health insurance subsidies benefit patients or producers? evidence from medicare advantage. *American Economic Review 108*(8), 2048–87.

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

Currie, J. (2006). The take up of social benefits. Poverty, the Distribution of Income, and Public Policy, pp. 80–148. New York: Russell Sage.

Curto, V., L. Einav, J. Levin, and J. Bhattacharya (2019). Can health insurance competition work? evidence from medicare advantage. Working paper, Harvard University and Stanford University.

Domurat, R., I. Menashe, and W. Yin (2019). The role of behavioral frictions in health insurance marketplace enrollment and risk: Evidence from a field experiment. Working Paper 26153, National Bureau of Economic Research.

Dubois, P., R. Griffith, and M. O'Connell (2018). The effects of banning advertising in junk food markets. *The Review of Economic Studies 85*(1), 396–436.

Electronic copy available at: https://ssrn.com/abstract=3434450

Duggan, M., A. Starc, and B. Vabson (2016). Who benefits when the government pays more? pass-through in the medicare advantage program. *Journal of Public Economics 141*(Supplement C), 50 – 67.

Finkelstein, A., N. Hendren, and M. Shepard (2019). Subsidizing health insurance for low-income adults: Evidence from massachusetts. *American Economic Review 109*(4), 1530–67.

Finkelstein, A. and M. J. Notowidigdo (2019). Take-Up and Targeting: Experimental Evidence from SNAP. *The Quarterly Journal of Economics 134*(3), 1505–1556.

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

Goldin, J., I. Z. Lurie, and J. McCubbin (2019). Health insurance and mortality: Experimental evidence from taxpayer outreach. Working Paper 26533, National Bureau of Economic Research.

Gollust, S. E., A. Wilcock, E. F. Fowler, C. L. Barry, J. Niederdeppe, L. Baum, and P. Karaca-Mandic (2018). Tv advertising volumes were associated with insurance marketplace shopping and enrollment in 2014. *Health Affairs 37*(6), 956–963.

Gordon, B. R. and W. R. Hartmann (2016). Advertising competition in presidential elections. *Quantitative Marketing and Economics 14*(1), 1–40.

Grossman, G. M. and C. Shapiro (1984). Informative advertising with differentiated products. *The Review of Economic Studies 51*(1), 63–81.

Hackmann, M. B., J. T. Kolstad, and A. E. Kowalski (2015). Adverse selection and an individual mandate: When theory meets practice. *American Economic Review 105*(3), 1030–66.

Handel, B., I. Hendel, and M. D. Whinston (2015). Equilibria in health exchanges: Adverse selection versus reclassification risk. *Econometrica 83*(4), 1261–1313.

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

Hastings, J., A. Hortaçsu, and C. Syverson (2017). Sales force and competition in financial product markets: The case of mexico's social security privatization. *Econometrica 85*(6), 1723–1761.

Hastings, J. S. and J. M. Weinstein (2008). Information, School Choice, and Academic Achievement: Evidence from Two Experiments. *The Quarterly Journal of Economics 123*(4), 1373–1414.

Ho, K. and R. S. Lee (2019). Equilibrium provider networks: Bargaining and exclusion in health care markets. *American Economic Review 109*(2).

Holmes, T. J. (1998). The effect of state policies on the location of manufacturing: Evidence from state borders. *Journal of Political Economy 106*(4), 667–705.

Karaca-Mandic, P., A. Wilcock, L. Baum, C. L. Barry, E. F. Fowler, J. Niederdeppe, and S. E. Gollust (2017). The volume of tv advertisements during the aca's first enrollment period was associated with increased insurance coverage. *Health Affairs 36*(4), 747–754.

Electronic copy available at: https://ssrn.com/abstract=3434450

Kosar, K. R. (2014). Advertising by the federal government: An overview. Congressional Research Service Report for Congress .

Lee, P. V., V. Pegany, J. Scullary, and C. Stevens (2017). Marketing matters: Lessons from california to promote stability and lower costs in national and state individual insurance markets. Technical Report, Covered California.

Lewis, R. A. and J. M. Rao (2015). The unfavorable economics of measuring the returns to advertising. *Quarterly Journal of Economics 130*(4), 1941–1973.

Li, X., W. R. Hartmann, and T. Amano (2020). Preference externality estimators: A comparison of border approaches and ivs. Working paper, Peking University, Stanford GSB, and Harvard Business School.

Moshary, S. (2017). Price discrimination across pacs and the consequences of political advertising regulation. Working paper, University of Pennsylvania.

Newhouse, J. P., M. Price, J. M. McWilliams, J. Hsu, and T. McGuire (2015). How much favorable selection is left in medicare advantage? *American Journal of Health Economics 1*(1), 1–26.

Polyakova, M. and S. Ryan (2019). Subsidy targeting and market power. working paper, Stanford Univertisy and Washington University in St. Louis.

Sen, A. P. and T. DeLeire (2018). How does expansion of public health insurance affect risk pools and premiums in the market for private health insurance? evidence from medicaid and the affordable care act marketplaces. *Health Economics 27*(12), 1877–1903.

Shapiro, B. (2018). Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of Political Economy 126*(1), 381–437.

Shapiro, B., G. J. Hitsch, and A. Tuchman (2019). Generalizable and robust tv advertising effects. Working paper, Chicago Booth and Northwestern kellogg.

Shepard, M. (2016). Hospital network competition and adverse selection: Evidence from the massachusetts health insurance exchange. Working paper, Harvard University .

Sinkinson, M. and A. Starc (2018). Ask Your Doctor? Direct-to-Consumer Advertising of Pharmaceuticals. *The Review of Economic Studies 86*(2), 836–881.

Spenkuch, J. L. and D. Toniatti (2018). Political Advertising and Election Results. *The Quarterly Journal of Economics 133*(4), 1981–2036.

Tebaldi, P. (2017). Estimating equilibrium in health insurance exchanges: Price competition and subsidy design under the aca. Working paper, University of Chicago .

Tuchman, A. E. (2019). Advertising and demand for addictive goods: The effects of e-cigarette advertising. *Marketing Science 38*(6), 994–1022.

Waldfogel, J. (2003). Preference externalities: An empirical study of who benefits whom in differentiated-product markets. *The RAND Journal of Economics 34*(3), 557–568.

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Online Appendix (Not For Publication)

A Discussion on the Border Strategy

Differences between Pairs of Border Counties Table 10 compares market characteristics between border counties with low and high government and private advertising spending, where government advertising is defined as the sum of federal and state advertising. For the first two columns, we collect border counties with lower government advertising spending within each border pair in Column (1) and border counties with higher government advertising spending within each border pair in Column (2). We excluded border pairs with zero government advertising in both sides of borders from the sample used to produce the table. For Columns (3) and (4), we group border counties similarly based on market-level private advertising spending.

The table shows that the two groups of markets are very similar in terms of market characteristics except for advertising spending. First, the number of insurers selling marketplace plans, the degree of market concentration (shown by HHI), and the market size are very similar between border counties with low and high advertising spending. Moreover, distributions of incomes and ages among potential enrollees are also very similar between the two groups of border counties. Lastly, health statuses measured by market-level shares of individuals with various health conditions are also almost identical between the two groups of border counties. These results suggest that the identifying assumption is plausible. Moreover, these results suggest that the targeting of advertising we documented in Section 3.3 is likely to be driven by non-border counties, which do not share advertising market borders.

Differences between Border and Non-Border Counties An important caveat about the border strategy is that estimated effects of advertising are local to border counties. Thus, it might be difficult to extrapolate the estimated effects to non-border counties, which are excluded from the estimation sample. To ascertain how serious this issue is in our setting, we compare market-level characteristics between border and non-border counties. Table 11 presents market-level characteristics between border and non-border counties. The table shows that although there are differences between the two groups of counties, the differences are small. For example, the differences in the number of insurers and HHIs do not exceed 10% of their unconditional averages. The distributions of ages and income groups are also similar between border and non-border counties. Lastly, the differences in county-level health statuses also do not exceed 10% of their unconditional averages. This

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Table 10: Comparing Either Side of Border Areas

	Gov Ad			Priv Ad
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Fed Spend ($)	0.218	0.515	0.243	0.275
	(0.199)	(0.487)	(0.329)	(0.377)
State Spend ($)	0.180	0.374	0.149	0.197
	(0.574)	(0.995)	(0.602)	(0.722)
Priv Spend ($)	0.918	1.111	0.567	1.624
	(1.413)	(1.513)	(0.890)	(1.948)
No. of Insurers	2.654	2.679	2.494	2.521
	(1.472)	(1.518)	(1.422)	(1.439)
HHI among Insuers	0.686	0.688	0.708	0.705
	(0.241)	(0.244)	(0.242)	(0.242)
Log of Market Size	8.485	8.533	8.398	8.446
	(1.226)	(1.266)	(1.210)	(1.244)
Share: Income $\leq$ 138% of FPL	0.242	0.240	0.244	0.243
	(0.089)	(0.086)	(0.088)	(0.089)
Share: Age $\geq$ 55	0.195	0.195	0.196	0.197
	(0.053)	(0.052)	(0.053)	(0.053)
Share: Poor or Fair Health	0.177	0.176	0.181	0.181
	(0.050)	(0.051)	(0.050)	(0.051)
Share: Obesity	0.315	0.314	0.319	0.318
	(0.042)	(0.042)	(0.042)	(0.043)
Share: Diabetes	0.115	0.116	0.118	0.118
	(0.024)	(0.023)	(0.024)	(0.024)
Healthcare Cost (in $1000s)	9.516	9.537	9.664	9.627
	(1.490)	(1.373)	(1.478)	(1.440)
N. Obs.	5,533	5,533	8,496	8,496

Note: This table compares market characteristics between border counties with low and high government and private advertising spending. Government advertising is defined as the sum of federal and state advertising. For the first two columns, we collect border counties with lower government advertising spending within each of border pairs in Column (1) and border counties with higher government advertising spending within each of border areas in Column (2). We excluded border pairs with zero government advertising in both sides of borders from the sample used to produce the table. For Columns (3) and (4), we group border counties similarly based on market-level private advertising spending. Standard errors are in parentheses.

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Table 11: Comparing Border and Non-Border Counties

	(1) Border Counties	(2) Non-Border Counties	(3) Overall
No. of Insurers	2.685	2.451	2.540
	(1.559)	(1.415)	(1.476)
HHI among Insuers	0.676	0.716	0.700
	(0.243)	(0.242)	(0.243)
Log of Market Size	8.754	8.376	8.521
	(1.623)	(1.241)	(1.412)
Share: Income $\leq$ 138% of FPL	0.229	0.240	0.236
	(0.082)	(0.087)	(0.085)
Share: Age $\geq$ 55	0.187	0.197	0.193
	(0.051)	(0.054)	(0.053)
Share: Poor or Fair Health	0.166	0.180	0.175
	(0.048)	(0.051)	(0.050)
Share: Obesity	0.309	0.318	0.315
	(0.042)	(0.042)	(0.042)
Share: Diabetes	0.109	0.117	0.114
	(0.022)	(0.024)	(0.024)
Healthcare Cost (in $1000s)	9.550	9.637	9.604
	(1.527)	(1.483)	(1.501)
N. Obs.	5,165	8,334	13,499

Note: This table presents market-level characteristics between border and non-border counties. Column (1) and (2) present characteristics of border and non-border counties, respectively. Column (3) present characteristics of all counties. Standard errors are in parentheses.

suggests that although estimates from the border strategy will not be exactly the same as ones based on the entire data sample, the estimates are unlikely to be very different from ones based on the entire sample.

B Supply-Side Specification and Estimation

In our empirical analysis, we assume that the cost of advertising for each insurer is observed advertising spending and the fixed (unobserved) cost, $C_{jmt}(ad^{p}_{jmt}) = ad^{p}_{jmt} + \triangle_{jmt}$.This specification allows us to recover an insurer's primitive in a straightforward manner. First, among firms with positive advertisement expenditures, we can recover profitabilityπ_{jmt} by imposing an insurer's first order condition. First, from consumer-side demand estimates, we can analytically calculate the marginal enrollment at the observed advertising level. Then, we can obtain the estimates of π_{jmt} nonparametrically from the first order condition. Among firms with zero advertisement expenditure, we need to recover $\triangle_{jmt}$ and π_{jmt} jointly. One approach is to specify the functional form of $\triangle_{jmt}$ (e.g., Goeree (2008)); an alternative is to use the moment inequality approach to identify bounds of the parameters. Although both approaches could be implemented, we chose to let insurers with positive baseline advertising spending re-optimize in the counterfactual to keep our analysis simple.

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C Content of Advertising

We use Amazon Web Services (AWS) to transcribe the video of each advertisement. AWS automatically translate transcripts of advertisements in Spanish into English. We then view a sample of advertisements and generate a list of keywords that characterize the contents of the advertisement. Each advertisement in the sample is then classified based on these keywords and a set of dummy variables indicating the presence of each type of content is generated. Although this approach is necessarily ad hoc, we find that it performs well in ex post manual verification. The list of content types and keywords are shown below:

- Reform: This dummy variable is equal to one if an advertisement contains at least one of the following terms: "affordable care act", "new law", "health care law", "health care reform law", "health care reform", "new health care", "reform", "health care act", "recent changes in health care", "changes that are coming in the health care system", "health care changes", or "changes in our health care".

- Open Enrollment:. This dummy variable is equal to one if an advertisement contains at least one of the following terms: "open enrollment", "deadline","choose or change plan", "last day", "enrollment period", "registration period", "open registration", "enrollment is now open", "February fifteen", "fifteenth of February", "December fifteen", "fifteen of December", "march thirty", "December 15", "January thirty first", "enroll-a-thon". If advertising contains "open enrollment for state and county employees","April thirtieth", then we assign the dummy to take zero.

- Uninsured: This dummy variable is equal to one if an advertisement contains at least one of the following terms: "uninsured", "still need health insurance", or "existing condition".

- Penalty: This dummy variable is equal to one if an advertisement contains at least one of the following terms: "penalty", "penalties", "the fine", "required to have health insurance", "required by law", "requirement", "required to have".

- Financial: This dummy variable is equal to one if an advertisement contains at least one of the following terms: "financial assistance", "financial help", "income information", "estimated income", "tax credit", "financial aid", "subsidy", "subsidies", "federal assistance", "government aid", "government to help", "money from the government", "qualify for assistance", "help pay", "help with their monthly payment",

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"eligible for money", "how much money you could get from the government", "government helping to pay", "federal help", "assistance to pay", "eligible for money", "getting money to help", "sum city", "financial health", "national assistance", "receive financial", "qualify for assistance", or "aid for your health insurance".

- ACA: this dummy variable is equal to one if at least one of dummy variables created above is equal to one.

D Additional Tables

Table 12: Targeting of Federal Advertising

	(1) ACA-related	(2) Financial	(3) Open Enrollment	(4) Penalty	(5) Reform
Share: Income $\leq$ 138% of FPL (%)	-0.001	-0.000	-0.000	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Medicaid Expanded=1	-0.098*	-0.043	-0.027	-0.001	-0.027
	(0.058)	(0.032)	(0.025)	(0.001)	(0.020)
Medicaid Expanded=1 $\times$ Share: Income $\leq$ 138% of FPL (%)	0.003	0.001	0.001	0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Share: Age $\geq$ 55 (%)	0.001	-0.000	-0.000	0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Share: Poor or Fair Health (%)	0.002	0.002*	0.002*	0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
No. of Insurers	0.017***	0.008**	0.001	-0.000	0.006**
	(0.006)	(0.003)	(0.002)	(0.000)	(0.002)
Log of Market Size	0.029***	0.007**	0.004	0.000	0.009**
	(0.008)	(0.003)	(0.002)	(0.000)	(0.003)
Year FE	Y	Y	Y	Y	Y
N. Obs.	784	784	784	784	784
Adj. R^2	0.148	0.466	0.542	0.017	0.366

Note: This table reports estimates of the coefficients in Equation (1). Each column presents estimates from the same specification with the dependent variable of federal spending on advertisements providing a specific message. Because there is no federal advertising spending in 2018, we restricted our sample years to 2014–2017. Standard errors are in parentheses and clustered at the DMA level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

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Table 13: Targeting of State Advertising

	(1) ACA-related	(2) Financial	(3) Open Enrollment	(4) Penalty	(5) Reform
Share: Income $\leq$ 138% of FPL (%)	-0.036***	-0.017***	-0.014***	-0.000	-0.003**
	(0.008)	(0.006)	(0.003)	(0.001)	(0.001)
Share: Age $\geq$ 55 (%)	-0.007	-0.004	-0.006	0.002*	0.000
	(0.014)	(0.011)	(0.005)	(0.001)	(0.000)
Share: Poor or Fair Health (%)	0.017	0.008	0.009*	0.001	0.003**
	(0.011)	(0.009)	(0.005)	(0.001)	(0.001)
No. of Insurers	0.091***	0.059***	0.042***	-0.003	-0.001
	(0.028)	(0.019)	(0.015)	(0.003)	(0.002)
Log of Market Size	-0.038	-0.027	0.013	0.012**	0.002
	(0.054)	(0.034)	(0.021)	(0.006)	(0.003)
Year FE	Y	Y	Y	Y	Y
N. Obs.	302	302	302	302	302
Adj. R^2	0.186	0.108	0.182	0.034	0.169

Note: This table reports estimates of the coefficients in Equation (1). Each column presents estimates from the same specification with the dependent variable of state spending on advertisements providing a specific message. Because there is no federal advertising spending in 2018, we restricted our sample years to 2014–2017. Standard errors are in parentheses and clustered at the DMA level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

Table 14: Targeting of Private Advertising

	(1) All	(2) ACA-related	(3) Financial	(4) Open Enrollment	(5) Penalty	(6) Reform
Share: Income $\leq$ 138% of FPL (%)	0.016**	0.008**	0.005**	0.004	0.007***	0.005**
	(0.008)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Medicaid Expanded=1	0.545**	0.195*	0.075	0.104	0.159***	0.087
	(0.224)	(0.099)	(0.075)	(0.077)	(0.051)	(0.061)
Medicaid Expanded=1 $\times$ Share: Income $\leq$ 138% of FPL (%)	-0.018**	-0.005	-0.003	-0.002	-0.006***	-0.003
	(0.009)	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)
Share: Age $\geq$ 55 (%)	0.017**	0.003	0.006**	0.003	0.004**	0.004**
	(0.008)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Share: Poor or Fair Health (%)	-0.008	-0.002	0.002	0.000	-0.003	0.000
	(0.008)	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)
No. of Insurers	0.059***	0.019***	0.012*	0.012**	0.001	0.006
	(0.015)	(0.007)	(0.006)	(0.006)	(0.004)	(0.005)
Log of Market Size	0.147***	0.074***	0.052***	0.054***	0.021***	0.028***
	(0.025)	(0.013)	(0.009)	(0.010)	(0.006)	(0.006)
Year FE	Y	Y	Y	Y	Y	Y
N. Obs.	983	983	983	983	983	983
Adj. R^2	0.212	0.210	0.178	0.165	0.131	0.288

Note: This table reports estimates of the coefficients in Equation (1). Each column presents estimates from the same specification with the dependent variable of private spending on advertisements providing a specific message. Because there is no federal advertising spending in 2018, we restricted our sample years to 2014–2017. Standard errors are in parentheses and clustered at the DMA level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

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Table 15: Coefficient Estimates by Demographic Group

	Age			Income		
	(1) 18 to 34	(2) 35 to 54	(3) ≥ 55	(4) $\leq 138\%$	(5) 138% to 250%	(6) 250% to 400%
Log of Fed Spend	0.030	0.093**	0.091*	0.104*	0.088	0.080
	(0.047)	(0.043)	(0.053)	(0.054)	(0.072)	(0.061)
Log of State Spend	-0.175	-0.120	-0.146	-0.015	0.000	-0.243**
	(0.127)	(0.093)	(0.103)	(0.140)	(0.181)	(0.116)
Log of Priv Spend	0.118**	0.105***	0.117***	0.116**	0.087*	0.026
	(0.053)	(0.040)	(0.043)	(0.047)	(0.046)	(0.044)
No. of Insurers	-0.341***	-0.431***	-0.427***	-0.323***	-0.436***	-0.399***
	(0.056)	(0.055)	(0.059)	(0.062)	(0.075)	(0.062)
No. of Insurers $\times$ No. of Insurers	0.021***	0.031***	0.027***	0.023***	0.036***	0.027***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.007)
FirmBorderYear FE	Y	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y	Y
FirmRatingYear FE	Y	Y	Y	Y	Y	Y
N. Obs.	35,864	35,772	35,662	35,578	34,258	35,538
Adj. R^2	0.894	0.914	0.911	0.899	0.895	0.891

Note: This table reports the estimates of the coefficients in Equation (7). For Columns (1)–(3), the dependent variables are calculated based on market shares for individuals aged from 18 to 34, from 35 to 54, and 55 or above. For Columnn (4)–(6), the dependent variables are calculated based on market shares for individuals with incomes below 138% of the federal poverty line (FPL), between 138% and 250% of the FPL, and between 250% and 400% of the FPL. We omitted those with incomes above 400% of the FPL because very few of them sign up for the marketplace. All specifications include Firm$\times$Border$\times$Year fixed effects, County fixed effects, and Firm$\times$Rating Area$\times$Year fixed effects. Standard errors are in parentheses and clustered at the DMA$\times$Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

Table 16: Coefficient Estimates: Interaction between Government and Private advertising

	(1)
Log of Fed Spend	0.110*
	(0.063)
Log of Priv Spend	0.102**
	(0.043)
Log of Fed Spend $\times$ Log of Priv Spend	0.020
	(0.075)
Log of State Spend	-0.050
	(0.078)
Log of State Spend $\times$ Log of Priv Spend	0.098
	(0.125)
No. of Insurers	-0.383***
	(0.050)
No. of Insurers $\times$ No. of Insurers	0.026***
	(0.005)
FirmBorderYear FE	Y
County FE	Y
FirmRatingYear FE	Y
N. Obs.	38,272
Adj. R^2	0.929

Note: This table reports the estimates of the coefficients in Equation (7). The specification for this table includes interaction terms between federal and private advertising. The specification include Firm$\times$Border$\times$Year fixed effects, County fixed effects, and Firm$\times$Rating Area$\times$Year fixed effects. Standard errors are in parentheses and clustered at the DMA$\times$Year level. The stars indicate: *** for p<0.01, ** for p<0.05 and * for p<0.1.

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