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ABSTRACT

Direct-to-consumer advertising is pervasive in US healthcare markets, but little evidence exists on the effects of advertising by hospitals, second only to drug manufacturers in medical marketing. Advertising may help facilities increase market share by stealing existing patients, expand the market for hospital care, or do both. Regardless, it has important public finance implications due to the large sums of taxpayer funds spent by federal and state governments to subsidize hospital operations and finance care through public insurance programs. This paper provides the first causal evidence, to our knowledge, on the market expansion effects of hospital advertising. To obtain causal estimates, we leverage the fact that spikes in political advertising significantly crowd out hospital advertising in the same market, motivating an instrumental variables design. Using claims data on the universe of Traditional Medicare beneficiaries, we find that advertising expands aggregate patient volume and spending on inpatient care – though to a modest degree (implied elasticities of 0.06 and 0.05, respectively). Although the overall effect of advertising on hospital outpatient care is muted, for-profit hospitals obtain higher outpatient Medicare volume and revenue with greater advertising. Across both care settings, therefore, Medicare spending increases with hospital advertising.

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1 Introduction

Healthcare advertising is pervasive in the US. In 2016, spending on direct-to-consumer advertising (DTCA) for healthcare services and products reached nearly $9 billion (Schwartz and Woloshin 2019). Although pharmaceutical advertising represents the largest share, hospitals have become a significant and growing segment of this spending. Hospital advertising accounts for $1.4 billion, the largest among providers, and has grown 258% since 1997 (Schwartz and Woloshin 2019). Despite the size and rapid growth in hospital advertising, little is known about its consequences on the use of hospital services and patient welfare. On the one hand, advertising can expand the aggregate use of hospital care by providing patients with information about available services and encouraging marginal patients to seek care. On the other hand, it may just reallocate patients across hospitals without increasing overall use or necessarily improving patient health. Understanding the impacts of hospital advertising is an important economic and policy question. Because taxpayer dollars fund a large share of hospital services through public insurance programs such as Medicare and Medicaid, an important open question for policymakers is whether advertising expands the market for hospital services, and if so, whether the incremental utilization is socially beneficial. This paper addresses this important gap in the literature by providing the first empirical evidence on the market expansion effects of hospital advertising.

To examine this question, we use novel television advertising data from Nielsen's Ad Intel database and measure hospital utilization using a 100% national sample of hospital billing claims for patients covered by Traditional Medicare, the U.S. federal insurance program for elderly individuals. Medicare is a useful setting due to its status as the largest single insurer in the US and the ability for Medicare beneficiaries to seek out medical services almost anywhere. The former has clear public finance implications, and the latter implies that Medicare beneficiaries can respond to advertising without the frictions facing the commercially insured (e.g., provider networks and tiered cost-sharing) or the uninsured.

Because hospital advertising decisions are endogenous, we implement an instrumental variable (IV) strategy first utilized by Sinkinson and Starc (2019) that leverages political advertising on local television stations to instrument for contemporaneous hospital advertising in the same market. High-profile US elections can be won via narrow margins, which generates strong incentives to invest heavily in political marketing – especially via traditional media, such as television. The social value of such advertising is debatable, but importantly, it also generates externalities by crowding out advertising for other goods and services. This media market feature provides the analytic traction for our identification strategy. Consistent with the prior literature on pharmaceutical advertising, we observe sharp declines in hospital ads during the peak of election season. These effects are also largest in markets where political advertising increases the most, which are typically the geographies experiencing the most contested races. We subsequently use this variation in hospital advertising exposure across markets and time to study the causal effects of hospital advertising on patient volume and spending for hospital care by Medicare beneficiaries.

We find that hospital advertising increases aggregate inpatient stays in the market, with those originating in the ED being the most responsive to DTCA activity. Specifically, a 10% increase in hospital advertising leads to around 9 additional inpatient stays per 100,000 beneficiaries, or an increase in utilization of approximately 0.6%. This implies an elasticity of 0.06. The corresponding elasticity of Medicare payments for inpatient care is 0.05. The estimated effects on outpatient care are also positive but imprecise, with ED visits being more responsive again. The imprecise effect on overall outpatient visits masks heterogeneity by hospital profit status, with large and precisely estimated effects at for-profit hospitals. Finally, advertising does not differentially benefit high or low quality hospitals, as measured by risk-adjusted readmission rates.

This paper makes several contributions. It provides the first comprehensive analysis of hospital advertising using national data, contributing to the broader literature on healthcare advertising, which has primarily focused on the pharmaceutical sector. An extensive literature finds that direct-to-consumer pharmaceutical advertising expands the market for prescription drugs by increasing overall use and also leads to substitution between competing brands (Alpert, Lakdawalla, and Sood 2023; Berndt et al. 1995; Shapiro 2018; Sinkinson and Starc 2019). Prior studies have also found an increase in physician visits because filling new prescriptions requires physician involvement (Eisenberg et al. 2022; Iizuka and Jin 2005). In contrast, there is little evidence on the effects of advertising by hospitals, despite the size and importance of hospital advertising.

Intuitively, advertising could shape patients' demand for hospital care differently than for pharmaceuticals. Patients are more price sensitive for pharmaceuticals than they are for services that hospitals typically provide, such as emergency care (Ellis, Martins, and Zhu 2017), so it is an empirical question whether and to what extent advertising can expand aggregate demand for hospitals. Similar to other markets, advertising may be a way for hospitals to influence patient perceptions of quality and thereby induce increased demand for their facility. However, patients are likely to have strong preferences for particular providers, based on their past experiences, health status, and geography, suggesting more limited scope for market stealing than in other markets. We estimate advertising elasticities that are economically meaningful but generally smaller than for pharmaceuticals which may reflect the more inelastic demand for hospital care.

Second, we advance the small literature on hospital advertising. Prior studies have descriptively examined the characteristics associated with hospital advertising (Town and Currim 2002; Ndumele et al. 2021). Few studies have attempted to estimate the causal effects of advertising on hospital service use. Kim and KC (2020) is closely related to ours but complementary in nature since it focuses on the business stealing effects of hospital advertising using data from Massachusetts and a discrete choice demand analysis. More recently, Yoon and Kim (2024) show that advertising expands the market for a specific new type of surgery. By combining the universe of Medicare hospital claims with a quasi-experimental research design, we provide the first large-scale causal evidence on the market expansion effects tied to hospitals' DTCA efforts.

Finally, this paper highlights an important spillover effect of political campaign spending. Because advertising space and capacity is limited, the timing and geographic targeting of political advertising crowds out other advertisers, including healthcare providers. We show that political advertising has meaningful effects on hospital care, adding to the literature showing its effects on pharmaceutical use (Sinkinson and Starc 2019) and other industries outside of healthcare (Moshary, Shapiro, and Song 2021). The literature has often overlooked these broader externalities, and interestingly, our estimates imply that political advertising modestly suppresses Medicare spending for hospital care through its negative impact on hospitals' own advertising.

The rest of the paper proceeds as follows: Section 2 describes the data used for this project. Section 3 presents the empirical strategy. Section 4 discusses our results and implications of our findings. We conclude in Section 5.

2 Data

2.1 Advertising exposure

Advertising data come from the Nielsen "Ad Intel" database provided by the Kilts Marketing Data Center at the University of Chicago. We focus on television advertising, by far the largest category of advertising used by hospitals (Kantar Media 2016). Television advertising purchases are made within media markets known as designated market areas (DMAs). Our sample includes 206 DMAs, covering all markets in the US except those in Alaska. Local TV advertising bought for a DMA is available only to residents of that DMA. Nielsen measures the exposure, or reach, of advertisements in a DMA using Gross Rating Points (GRP), which measure advertising "impressions," instances of ads being displayed to users, per capita in a given DMA. Previous studies have found this to be a more reliable measure of advertising exposure than the amount spent (Alpert, Lakdawalla, and Sood 2023).

We focus on hospital and political advertising aired during the 2016 presidential election season, which we define to span from January 2015 through November 2016. Nielsen has a separate category for hospital advertising, so these are identified directly. We aggregate all advertising by hospitals to the DMA-month-year, the unit of analysis. We include political advertising from different types of races, including federal political office (President/Senate/House of Representative), state political office (e.g., Governor/Mayor/judges), and statewide ballot measures. As recommended by Moshary, Shapiro, and Song (2021), we also include ads from independent political action committees (henceforth, "superPACs"). Figure A.1 shows the distribution of spending across different types of political races. In both 2015 and 2016, political advertising is widely distributed across different types of political races and is not dominated by one category.

2.2 Hospital use and spending

We use administrative enrollment and billing claims data from the universe of Medicare fee-for-service (FFS) ("Traditional" Medicare) beneficiaries to measure hospital use and spending. Specifically, we construct monthly measures of hospital patient volume and mean spending per beneficiary on inpatient and outpatient care, aggregating up to the DMA level by mapping hospitals to the DMA they are located in. In our Medicare claims sample, we find that approximately 90% of patients choose a hospital located in the same DMA as their residence. This implies that the vast majority of patients represented in our DMA-level volume and spending measures reside in the same DMA.

Since markets vary substantially in their population size and in the number of FFS beneficiaries, we normalize patient volume counts to be expressed per 100,000 FFS beneficiaries residing in the DMA. Similarly, we express spending in dollars per beneficiary per month. This includes both Medicare spending and cost sharing by the beneficiary. Finally, we use data on the characteristics of FFS beneficiaries in the DMA to construct time-varying covariates at the market level. We include them in our regression models to control for the differences in the composition of beneficiaries across markets.

2.3 Supplementary data

We combine the primary data on advertising and hospital utilization with variables from other datasets to construct covariates and stratification measures. Hospital information, including bed size, number of hospitals and nonprofit status, comes from the American Hospital Association (AHA) annual surveys. Data on hospital clinical quality (30-day risk-adjusted readmission rates) come from the Hospital Compare portal maintained by the Centers for Medicaid and Medicare Services (CMS). We obtain monthly county-level unemployment data from the Federal Reserve Economic Data (FRED), which we aggregate to the DMA level using a population-weighted average. We use county-level population data from the American Community Survey to express market covariates in per capita terms.

2.4 Descriptive evidence

Table 1 presents key descriptive statistics from our analysis sample. The sample is a balanced panel of 206 DMAs over 23 months from January 2015 through November 2016, and thus contains 4,738 DMA-months. We limit the sample period to end in November 2016 to coincide with the US general election, since our instrumental variable design leverages the political advertising cycle. Panels A and B describe advertising exposure and hospital outcomes, respectively. Panels C and D describe the characteristics of Medicare FFS beneficiaries and hospitals in our sample, respectively.

All panels except Panel A report values calculated over 2015 so they indicate the baseline before the onset of the election season. For Panel A, we compare GRPs in both the pre-presidential election year (2015) and the presidential election year (2016). The goal is to highlight the changes in political and hospital advertising between these two years. Column 1 presents the mean values and standard deviations for all markets. Columns 2 and 3 report the corresponding values for the subsets of DMAs that have above-median and below-median exposure to hospital advertising, measured by GRPs. This helps shed light on differences in characteristics between markets with high versus low levels of hospital advertising.

Panel A provides intuition for the instrumental variable design. The mean exposure to political advertising increased nearly 600% from 776 to 4,731 GRPs between 2015 and 2016. In contrast, hospital advertising *decreased* 14% from 1,158 to 995 GRPs in those same years. A similar pattern is also observed in markets with high and low levels of exposure to hospital advertising. This evidence is consistent with a crowding out of hospital advertising due to the large increase in political advertising.

Panel B shows that hospital use and spending per beneficiary are remarkably similar in markets with high and low levels of hospital advertising, despite the large difference in exposure. In fact, the levels of hospital use and spending are slightly higher in markets with lower advertising exposure. The next two panels help interpret these patterns. Panel C shows that markets with higher level of advertising have much larger populations on average, though the composition of beneficiaries seems similar on a range of attributes. Finally, Panel D shows that markets with higher advertising exposure have, consistent with their larger population, nearly three times as many hospitals. As a result, concentration levels, denoted by the Herfindahl-Hirschman Index (HHI), are much lower in these markets.

The evidence above implies that more populated markets have much higher levels of exposure to advertising per capita. While the average market experienced a hospital advertising exposure of 1080 GRPs, the average Medicare FFS beneficiary resides in a market with 1532 GRPs, or nearly 50% higher exposure. Appendix Figure A.2 explores this pattern further. Panel (a) presents a binned scatter plot of the mean advertising GRPs in 2015 on the Y-axis against the corresponding 2015 mean number of FFS beneficiaries on the X-axis for 20 equal sized bins, each representing approximately 10 markets. Markets in the 8 smallest bins by population have very low advertising exposure. Panel (b) plots histograms of mean 2015 annual advertising exposure separately for markets below and above the median number of FFS beneficiaries in 2015, which is approximately 150,000. The plot shows that advertising exposure is concentrated at low levels in small markets, while there is significant variation in advertising in larger markets. This feature of hospital advertising motivates our decision to weight markets in regression models by the number of FFS beneficiaries, held fixed as of January 2015. Our regression coefficients should therefore be interpreted as estimating the effects of hospital advertising for the market in which the average FFS beneficiary resides, which is larger in population than the (unweighted) average market.

3 Empirical Strategy

3.1 The potential for bias

Our goal is to estimate the causal effect of hospital television advertising, H_{mt}, in market m and time t on hospital use and spending during the same period, denoted Y_{mt}. As discussed previously, we use DMAs to define advertising and healthcare markets and month-year as the unit of time. Equation 1 below represents our model of interest.

$$Y_{mt} = \alpha_m + \alpha_t + \beta H_{mt}[+\delta_1 X_{mt}] + \epsilon_{mt}. \tag{1}$$

The model includes market and time fixed effects and additional time-varying market-level covariates (e.g., the unemployment rate) to control for observed differences between markets. The coefficient of interest is β. However, estimating this model via OLS would likely recover a biased estimate of β due to unobserved factors that could be correlated with both advertising and hospital use. Two examples of reverse causality illustrate this concern. Higher quality hospitals will have greater financial resources due to higher patient volume and spending (Chandra et al. 2016). They may deploy their financial resources to purchase more advertising than their competitors. This would result in greater advertising levels in markets with greater hospital volume. An OLS estimate would be biased upward and overstate the true effect of advertising on hospital use. The second example makes the case for bias in the opposite direction. Hospitals may strategically time their advertisements to boost utilization in periods when they anticipate low patient demand due to shocks unobserved to the econometrician. In this case, an OLS estimate of the effect of advertising would be biased downward. There could be other sources of bias as well. Ex-ante, it is difficult to predict the sign of the net bias. Hence, to obtain the causal effects of advertising on hospital use, we need a plausibly exogenous source of variation in hospital advertising.

3.2 Instrumental variable approach

Our empirical strategy leverages plausibly exogenous shocks to hospital advertising due to the election cycle. We follow Sinkinson and Starc (2019), who used political advertising as an instrument to study the effects of drug advertising. Political advertising in the United States cycles through four-year periods, with races for governors and the presidency occurring every four years and races for the House of Representatives and one-third of the Senate occurring every two years. The main election is held in November every year, with primary elections scattered throughout the remainder of the year. The political parties and government of each state determine the timing and format of the primary and general elections in that state. This electoral system generates geographic and temporal variation in the intensity of political advertising, with spikes in more politically competitive markets closer to November. Such temporary increases in political advertising can crowd out other advertisers, including hospitals, making political advertising a source of plausibly exogenous shocks to hospital advertising.

Patterns in raw advertising data support the hypothesis that political advertising crowds out hospital advertising. Figure 1 demonstrates this possibility in the months leading up to the 2016 election. It presents the differences in advertising GRPs in each month between 2015, a non-presidential election year, and 2016, a presidential election year, for both political and hospital advertising. We scale the difference in each month by the corresponding difference in January, which is set to 100.[1] Political advertising starts to increase in July 2016 relative to the same month in 2015 and peaks in October, just before the election, at nearly 800, or 8$\times$ the January-to-January differential. This pattern is intuitive, as 2016 is an election year with more and higher profile political races than in 2015. In contrast, the relative trend for hospital advertising turns negative in 2016 compared to 2015 in the fall months, and particularly sharply in October. This dynamic

1. For completeness, Figure A.3 presents the raw trends in advertising in 2015 and 2016. Panels (a) and (b) present the trends for political and hospital advertising, respectively.

demonstrates the crowding out of hospital ads by political ads during the peak election advertising season.

Geographic patterns in advertising changes between 2015 and 2016 show that changes in political and hospital advertising are often negatively correlated within markets. Figure A.4 presents a heat map of the change in mean advertising units between 2015 and 2016 for all DMAs in the US. We compute the mean number of GRPs from May through October in the DMA in each year. DMAs are color coded according to their quartile of the difference in GRPs between the two years. Panels (a) and (b) present the patterns for political and hospital advertising, respectively. Panel (a) shows that political advertising increased in states that had competitive or high-profile races. For example, Arizona and California had high-profile senate races while Pennsylvania, Michigan, Wisconsin, and Ohio were considered swing states in the presidential election. Some states, such as North Carolina and Florida, fell in both categories. Most DMAs in these states are in the top two quartiles of change in political advertising, implying that they experienced the greatest increases. Strikingly, Panel (b) shows that a large fraction of DMAs in these states also lie in the bottom two quartiles of change in hospital advertising. Together, the contrasting temporal and geographic patterns in the raw data support the hypothesis that political advertising crowds out hospital advertising, suggesting its use as an instrument. Similarly, Moshary, Shapiro, and Song (2021) showed that political advertising is highly predictive of advertising by healthcare providers.

We estimate the first stage model shown in Equation 2, using political advertising GRPs, P_{mt}, to predict hospital advertising GRPs, H_{mt}, in the same market and month-year. The coefficient of interest in this model is π.

$$H_{mt} = \xi_m + \xi_t + \pi P_{mt}[+\delta_2 X_{mt}] + \eta_{mt}. \tag{2}$$

We use this model to obtain fitted values of hospital advertising, $\hat{H}_{mt}$, which then replace the observed values, H_{mt}, in Equation 1. In practice we estimate both models simultaneously using two stage least squares (2SLS) and obtain the causal effect parameter, β. The simplest models include DMA and month-year fixed effects. We also estimate models that include a time-varying vector of market-level controls, X_{mt}. This vector controls for differences across markets in the per capita share of Medicare beneficiaries, dually eligible Medicare beneficiaries, low-income subsidy recipients, and the average age of Medicare beneficiaries in the DMA. We also include the median unemployment rate in the DMA as a signal of the economic environment. We cluster standard errors by DMA, which is the level of treatment.

3.3 Instrument Validity

Identification is based on three standard IV assumptions. First, we require that changes in the instrument, political advertising, strongly predict changes in the endogenous variable, hospital advertising, after conditioning on market and month-year fixed effects. This is empirically testable, and we show that this condition is met in our data. Second, we must assume conditional independence between the instrument and unobserved factors that could affect the outcomes of interest. This assumption subsumes the exclusion restriction, which requires that political advertising affects hospital use and spending only through its effect on the level of hospital advertising. This assumption is untestable, but we present evidence to support its plausibility. Finally, we must assume monotonicity, that is, an increase in political advertising weakly decreases hospital advertising in all markets. This assumption is also untestable, but it is plausible in this setting, since the two advertiser types – hospitals and political campaigns – compete for the same time slots on television channels.

We begin by presenting the relationship between political and hospital advertising non-parametrically. Figure 2 Panel (a) shows a binned scatter plot of hospital advertising on the Y-axis against political advertising on the X-axis. Observations are demeaned by DMA and month-year, and then collapsed to 20 equal-sized bins. The plot presents the mean values in each bin, which clearly show a negative linear relationship between political and hospital advertising within-market. We overlay the scatter plot with a fitted line that is estimated on the underlying data. The slope of the fitted line is -0.013 and is precisely estimated.

Table 2 columns 1 and 2 present the coefficient on political advertising from the first stage model in Equation 2. Column 1 presents the results from a parsimonious model which includes only DMA and month-year fixed effects. The coefficient is precisely estimated and implies that an increase of 4,000 GRPs in political ads, approximately the mean increase observed between 2015 and 2016 (see Table 1A), is associated with a decrease of 52 GRPs of hospital ads (4000 x 0.013), approximately 30% of the observed decrease in mean hospital advertising between 2015 and 2016. Hence, political advertising appears to meaningfully crowd out hospital advertising. The table also presents the f-statistic from the first stage, 20.7, which is higher than the conventional thresholds for weak instruments (Stock and Yogo 2002; Olea and Pflueger 2013).

To assess the plausibility of conditional random assignment, we test the robustness of the first stage coefficient to the inclusion of time-varying covariates that could influence hospital use. Table 2 Column 2 presents the results from this model and shows a negligible change in the coefficient on political advertising relative to the model without covariates. Furthermore, and crucially for the validity of our design, the covariates appear to be uncorrelated with the instrument. This takeaway is confirmed by column 3, which shows that the market-level covariates are individually and jointly statistically insignificant (p-value of 0.68) in predicting political advertising.

4 Results

4.1 Average effects of hospital advertising

Table 3 presents the OLS and IV estimates of the effect of advertising on hospital use and spending. We consider seven outcomes of interest related to utilization and spending per beneficiary at the DMA level. Column 1 presents the weighted mean values for these outcomes. Columns 2 and 3 present the coefficients from the OLS model in Equation 1. To test sensitivity to controlling for differences in market characteristics, we present results from models without (column 2) and with (column 3) DMA-month year-level covariates. The next two columns present the corresponding IV coefficients obtained using political advertising as an instrument. Columns 4 and 5 present coefficients from models that exclude and include covariates, respectively. All coefficients should be interpreted as estimating the effect of a 1 GRP increase in hospital advertising. Finally, column 6 presents the short-run elasticity of advertising for each outcome, calculated at the mean, that is implied by the IV coefficient reported in column 5.

Inpatient care

We begin by examining the effects of advertising on the use of inpatient care. We study three measures of inpatient care: all stays, inpatient stays that originate in the emergency department (ED), and the mean spending per beneficiary on inpatient care. As described previously, measures of patient volume are expressed per 100,000 beneficiaries. Since the outcomes are calculated at the market level, the coefficients should be interpreted as estimating the aggregate market expansion effect on hospital care net of any business-stealing effects.

Although subject to the bias concerns discussed previously, the OLS results serve as a benchmark for the IV coefficients. The estimates in columns 2 and 3 are small in magnitude and statistically insignificant for all inpatient care outcomes and imply a *negative* relationship. For example, the coefficient in the first row of Column 3 implies that a 10% increase in hospital advertising (153 GRPs) is associated with a decrease of 0.2 stays (0.0012 x 153), approximately a change of 0.01% compared to the mean number of hospital stays of 1,510.

In contrast, the IV coefficients in columns 4 and 5 are uniformly positive in sign, implying that advertising increases the aggregate use of inpatient care. They are also an order of magnitude larger than the corresponding OLS estimates, suggesting that the OLS estimates are biased downward. The IV coefficients are precisely estimated in the case of volume and are marginally significant in the case of mean spending. Figure 2 Panels (b), (c), and (d) present binned scatter plots non-parametrically depicting the reduced form relationship between political advertising and inpatient care. Consistent with the IV coefficients, these figures show a decreasing relationship between hospital care and political advertising. In all three figures, the slope coefficient of a linear fit using the underlying market-level data is precisely estimated.

The IV estimates imply modest short-run elasticities of aggregate inpatient care use or spending with respect to television advertising. The coefficient in the first row of column 5 implies that an increase in hospital advertising of 10% leads to 9.1 additional inpatient stays per 100,000 beneficiaries (153 x 0.059), approximately a 0.6% increase relative to the mean. The implied elasticity of inpatient care with respect to advertising, therefore, is 0.06. Inpatient stays originating in the ED are slightly more responsive to television advertising, with an elasticity of 0.074, while mean spending on inpatient care has a slightly lower elasticity with respect to advertising of 0.05.

Our elasticity estimates for inpatient care lie in the middle of the range of previous estimates from studies of advertising of healthcare products. Kim and KC (2020) report a short-run own-elasticity of advertising of 0.023 using Massachusetts hospital discharge data. Notably, they use a different research design and Medicare patients make up only 40% of their sample. Non-Medicare patients have less need for inpatient care and typically have more restrictive insurance coverage than FFS beneficiaries, which may constrain their hospital choices. Kim, Kim, and Yoon (2023) and Yoon and Kim (2024) estimate slightly higher short-run advertising elasticities of approximately 0.035 for ED visits and robotic surgeries, respectively, using hospital data from Florida. Shapiro (2018) reports an own-elasticity of 0.02-0.04 for anti-depressant drugs. Using a similar research design as ours (leveraging the 2008 election cycle), Sinkinson and Starc (2019) estimate an own-elasticity of 0.08-0.14 for branded statin drugs. However, they report a much lower category-level advertising elasticity of 0.013. Tuchman (2019) reports an elasticity of 0.08-0.16 for e-cigarette advertising. At the higher end, Alpert, Lakdawalla, and Sood (2023) report an elasticity of aggregate demand for chronic drugs among Medicare beneficiaries of 0.54.

Outpatient and ED care

Table 3 also presents results on the effects of advertising on hospital outpatient and ED care. The general patterns of these coefficients are similar to those of inpatient care discussed above: small and negative OLS estimates but positive and much larger IV coefficients. However, the IV coefficients and elasticities related to outpatient and ED care are not precisely estimated at conventional levels of significance. For completeness, Figure A.5 presents the corresponding reduced form binned scatter plots. Among these outcomes, the most responsive to advertising appears to be demand for outpatient ED care, with a short-run elasticity of 0.05.

Interpretation

The results on inpatient and outpatient care collectively suggest that hospital advertising draws patients to the ED who otherwise would not have used hospital services. This could occur if, for example, advertising persuades elderly individuals to prefer the hospital ED instead of going to an urgent care clinic. Since almost 90% of FFS Medicare beneficiaries have some form of secondary coverage which limits their out of pocket payments (Ochieng, Cubanski, and Neuman 2024), they are largely sheltered from the additional costs associated with switching to a hospital.

Our baseline models estimate the relationship between advertising and hospital use in the same month. We briefly assess the possibility of advertising affecting future demand by estimating an alternate model that follows the approach of Yoon and Kim (2024). We model hospital outcomes as functions of the average of advertising GRPs in the current and previous months. The results of this exercise are presented in columns 4 and 5 of Table A1. The corresponding elasticities are slightly larger in magnitude, although less precise. The increased magnitude suggests that advertising also affects patient choices in the next month, however the imprecision of these estimates suggests that most of the effect is driven by contemporaneous advertising.

4.2 Heterogeneous effects

Since our research design leverages changes in political advertising at the market level, we can only instrument for market-level hospital advertising. However, we can quantify whether the market expansion effects of advertising differ for hospitals of different types. Specifically, we explore along two dimensions of policy interest: clinical quality and profit status. If advertising differentially expands volume at high-quality hospitals, it would be considered socially beneficial. The welfare implications of a shift in volume between for-profit and nonprofit hospitals are less clear but still of great interest due to ongoing debates over the role of both types of organizations in healthcare and the tax-exempt status of nonprofits (Duggan 2000; Horwitz and Nichols 2022).

We explain the approach by taking the example of for-profit status. First, we limit the sample to DMAs which contain both nonprofit and for-profit hospitals, with government hospitals considered nonprofits. This restriction reduces the sample from 206 to 138 markets, but ensures that the coefficients for the two profit types are directly comparable. These results are not comparable to those in Table 3 since these 138 markets tend to be more urban and larger in population. Next, we estimate our baseline IV models as before, except that the outcomes represent aggregate patient volume and mean spending separately for nonprofit and for-profit hospitals, respectively. The advertising measure remains the total GRPs across all hospitals in the DMA, as in the main analysis. Hence, this approach separately estimates the market expansion effects of advertising for nonprofit and for-profit hospitals.

The analysis testing heterogeneity by hospital quality is conceptually similar but more involved since we must first assign hospitals to high, medium, or low quality. We focus on hospital risk-adjusted 30-day readmission rates, which we obtain from CMS, as our measure of quality. Readmission rate is a standard quality measure commonly used in the literature to assess hospital quality (Chandra et al. 2016; Dharmarajan et al. 2017) and by the federal government to incentivize hospitals to improve quality (Gupta 2021). We deem hospitals with risk-adjusted readmission rates in the bottom quartile in their DMA as high quality. In contrast, hospitals in the top quartile of their DMA are deemed of low quality (since higher readmission rates are undesirable). The remaining hospitals are considered to be of medium quality. We limit the analysis sample for this exercise to the 163 markets that contain all three groups of hospitals so that the corresponding coefficients can be meaningfully compared.[2]

Table A2 presents the corresponding results of these two analyses. We consider the same outcomes as in the main analysis presented above. Columns 1–3 present the effects separately for hospitals assigned to different quality categories, while Columns 4 and 5 present the effects by profit status. For brevity, we present results only from the IV model including time-varying market-level covariates.

With regards to inpatient care, there does not appear to be significant heterogeneity in the effects of advertising either on quality or by profit status. The magnitudes are similar across hospital categories, although some are imprecisely estimated. The results on outpatient care are more indicative of heterogeneity in the effects of advertising, particularly by profit status. We find large and statistically significant increases in outpatient volume and mean spending at for-profit hospitals, but the coefficients for nonprofit hospitals are small. The results on outpatient ED volume also indicate much greater market expansion effects among for-profits, and to some extent for higher quality hospitals.

Taken together, the results do not imply that advertising steers patient demand for hospital care toward high or low quality hospitals, as measured by readmission rates. On the other hand, they do imply that television advertising differentially increases outpatient and ED patient volume

2. A hospital must meet certain criteria for CMS to publicly report its risk-adjusted readmission rate on Hospital Compare.

at for-profit hospitals.

5 Conclusion

This paper leverages an IV design to estimate the causal effects of television advertising on the use of hospital services and spending by Medicare FFS beneficiaries. Overall, our results imply that hospital advertising expands aggregate demand for inpatient stays and spending by Medicare beneficiaries. The effect appears to be driven by greater demand for ED care, which leads to more hospital admissions. We estimate a short-run elasticity of aggregate hospital stays with respect to advertising views of about 0.06, and an elasticity of inpatient spending of 0.05. These estimates are lower than those for prescription drugs and e-cigarettes reported in previous studies. If hospital advertising induces patients to turn to costly ED use instead of alternatives like urgent care clinics or primary care, it may represent inefficient care, and use of taxpayer dollars in the case of Medicare. This concern highlights the need to comprehensively examine the impact on patient welfare, which was outside the scope of this paper.

There are several other avenues for future work. Our empirical strategy leverages variation in hospital and political advertising at the market level, and hence we cannot study the business stealing effects of advertising. This is an important next step in quantifying the return on investment to the advertising hospital. Our utilization and spending data is limited to Medicare FFS beneficiaries and, therefore, our results relate most directly to this group. Medicare is the single largest payer of hospital care in the US by patient volume and contributed approximately 40% of hospital patients during this period (McDermott, Elixhauser, and Sun 2017). However, these results may not be representative of the effects for privately insured patients who, for example, face greater restrictions in provider choice. Hence, researchers should continue to build the evidence base on hospital advertising by examining other patient groups.

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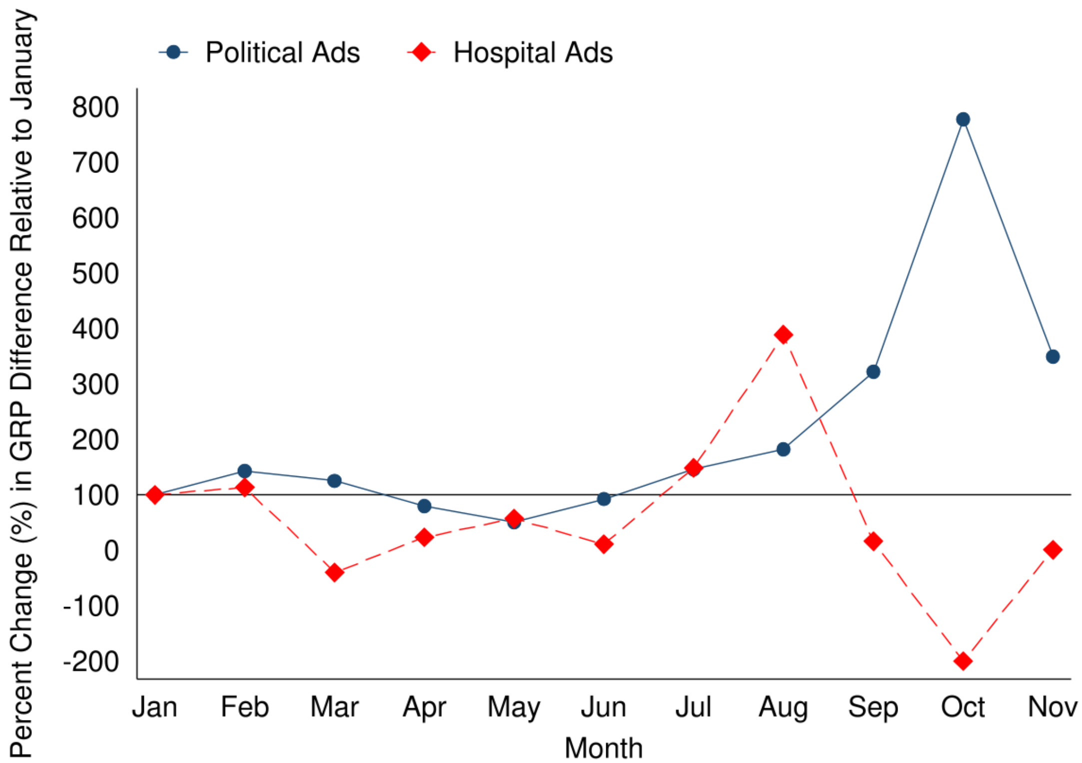
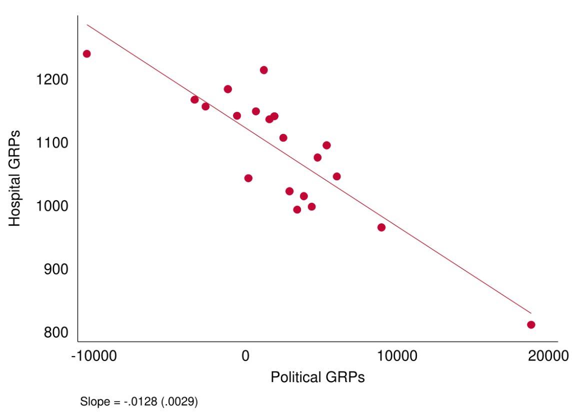
Figure 1: Change in advertising units in 2016 relative to 2015 by month

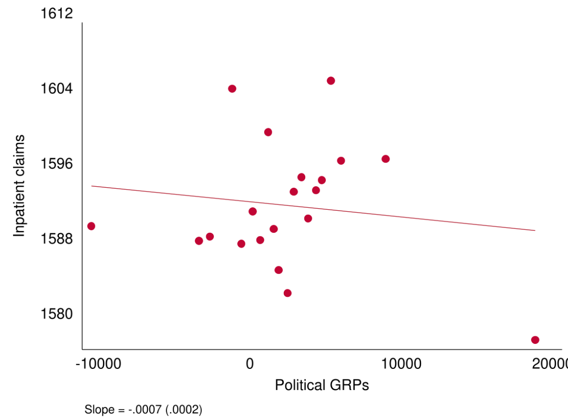


Note: The figure presents in each month the difference in the mean number of advertising units, measured in gross rating points (GRPs), between 2015 and 2016. We normalize each value against the corresponding difference between January 2015 and 2016 in order to highlight the sharp changes in advertising during the presidential election. For example, political advertising increased 800% between 2015 and 2016 in October relative to the change in January, while hospital advertising decreased nearly 200%. This illustrates the underlying variation leveraged by the instrumental variable design.

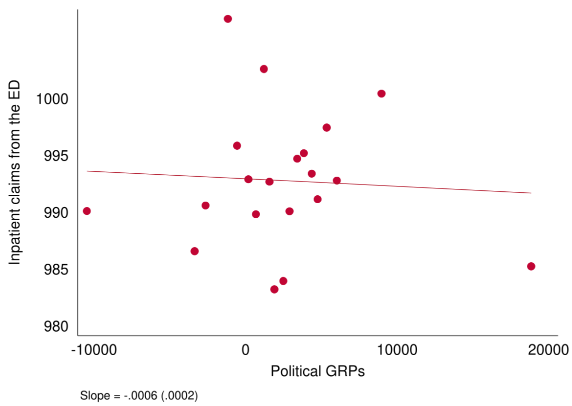
Figure 2: First stage and reduced form variation



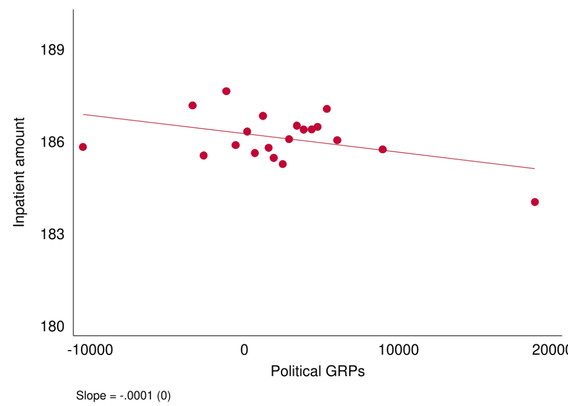
(a) First Stage



(b) Inpatient claims (all)



(c) Inpatient claims (from the ED)



(d) Inpatient allowed amount

Note: The figure presents binned scatter plots to visually depict the first stage (Panel a) and reduced form outcomes pertaining to inpatient care (Panels b, c, and d), respectively. In each plot, the dots represent mean values for 20 equal-sized bins. We also overlay a fitted line estimated using OLS on the underlying market-level data, weighting markets by the number of FFS beneficiaries as of January 2015, and report the slope coefficient and its standard error below the plot. Panel (a) plots the first stage relationship between hospital advertising gross rating points (GRPs) on the Y-axis versus political advertising on the X-axis. Panel (b) plots the relationship between inpatient claims for Medicare FFS patients expressed per 100,000 beneficiaries, on the Y-axis versus political advertising on the X-axis. The outcomes in Panels (c) and (d) are inpatient claims admitted from the ED and mean spending on inpatient care per beneficiary, respectively. All Y axes are centered around the mean value. Figure A.5 presents corresponding plots for outpatient care.

Table 1: Summary Statistics

	(1) Full Sample	(2) Above median	(3) Below Median
A: Advertising			
Hospital GRPs			
2015	1,158.05	2,029.02	287.08
	(1,339.16)	(1,383.74)	(393.68)
2016	995.40	1,726.40	264.39
	(1,184.59)	(1,254.48)	(405.40)
Political GRPs			
2015	775.87	1,178.56	373.17
	(2,689.65)	(3,403.21)	(1,602.44)
2016	4,730.89	6973.5	2,488.28
	(8,843.07)	(10,830.71)	(5,394.19)
B: Hospital use and spending per beneficiary			
Inpatient claims (all)	1,615.13	1,515.59	1,714.66
	(460.83)	(354.51)	(528.57)
Inpatient claims (ED)	1,006.69	968.89	1,044.50
	(371.48)	(297.23)	(430.00)
Inpatient allowed amount ($)	186.04	181.38	190.70
	(68.57)	(44.44)	(85.95)
Outpatient claims (all)	22,495.32	19,841.94	25,174.70
	(10,646.75)	(8,432.89)	(11,907.96)
Outpatient allowed amount ($)	96.73	88.46	105.08
	(37.40)	(30.48)	(41.66)
Outpatient claims (ED)	2,536.62	2,350.56	2,724.51
	(754.54)	(581.01)	(856.45)
ED allowed amount ($)	10.61	9.99	11.24
	(3.38)	(2.67)	(3.87)
C: Medicare beneficiary demographics			
Number of beneficiaries	270,936	430,820	111,051
	(386,462)	(476,918)	(142,154)
Fraction dual eligible	0.18	0.18	0.18
	(0.06)	(0.05)	(0.06)
Fraction low-income subsidy eligible	0.22	0.22	0.22
	(0.06)	(0.06)	(0.07)
Average age	70.72	70.78	70.66
	(1.06)	(1.08)	(1.05)
D: Hospital attributes			
Number of hospitals	19.52	28.47	10.58
	(19.27)	(22.06)	(9.83)
Proportion nonprofit	0.67	0.70	0.64
	(0.29)	(0.24)	(0.33)
Average number of beds	168.39	188.33	148.44
	(81.13)	(68.87)	(87.35)
Herfindahl-Hirschman Index	2,131.05	1,209.21	3,052.89
	(1,909.82)	(1,060.86)	(2,114.57)
Number of DMAs	206	103	103

Note: The table presents summary statistics for the analysis sample. Unless otherwise specified, the values are calculated using data from January–December 2015. Column 1 presents values for the full sample of 206 designated market areas (DMAs), the standard market definition for television ads. Columns 2 and 3 present the corresponding values for markets with above- and below-median hospital advertising units, respectively. For each variable, we present the mean in the top row and the standard deviation in the bottom row. GRP refers to gross rating points and is our preferred measure of advertising units. Medicare utilization outcomes in Panel B pertain to fee-for-service (FFS) beneficiaries only. The number of claims is scaled by 100,000 Medicare FFS beneficiaries to account for differences in population size across markets. Allowed amounts are expressed as per FFS beneficiary per month. The Herfindahl-Hirschman Index in Panel D is calculated using hospital shares in a DMA in terms of the number of beds. Data on hospital beds and profit status are sourced from the American Hospital Association annual surveys.

Table 2: First stage and instrument balance

	(1) Hospital GRPs	(2) Hospital GRPs	(3) Political GRPs
Political GRPs	-0.0128***	-0.0130***	
	(0.0028)	(0.0028)	
Beneficiaries per capita		518.1	841.2
		(1748.5)	(8745.3)
Dual eligible per capita		1003.7	10920.9
		(1022.7)	(11748.8)
LIS eligible per capita		-795.1	-9280.5
		(1545.0)	(13277.0)
Average age of beneficiaries		468.0	4287.5
		(660.0)	(6855.1)
Median unemployment rate		-15.2	-1181.9
		(73.0)	(756.7)
Constant	1579.4***	1198.1***	5852.8
	(10.5)	(545.0)	(4225.8)
DMA fixed effects	X	X	X
Month-year fixed effects	X	X	X
Dep. Var. mean	1,531.93	1,531.93	3,742.55
Dep. Var. SD	1,246.25	1,246.25	8,220.25
First stage f-test statistic	20.66	21.08	
Joint test of significance p-value			0.68
Observations	4,738	4,738	4,738

Note: The table presents the first stage results and evidence on instrument balance. Column 1 presents the results from the first stage model including DMA and month-year fixed effects. Column 2 presents the corresponding coefficients when we also include time-varying covariates at the DMA by month-year level. The covariates are number of Medicare FFS beneficiaries per capita, number of dual eligible FFS beneficiaries per capita, number of Low-income subsidy eligible beneficiaries per capita, mean FFS beneficiary age, and the median unemployment rate across counties that make up the DMA. Unemployment rate information comes from Federal Reserve Economic Data (FRED) on county level unemployment. Covariate values are standardized to have mean zero and SD of 1 so their coefficients indicate the effect of a 1 SD increase. We present the corresponding f-test statistics. Column 3 presents the correlation between market covariates and the instrument, political advertising. We also present the p-value from a joint test of significance across all covariates. Standard errors are clustered by DMA and are presented in parentheses.

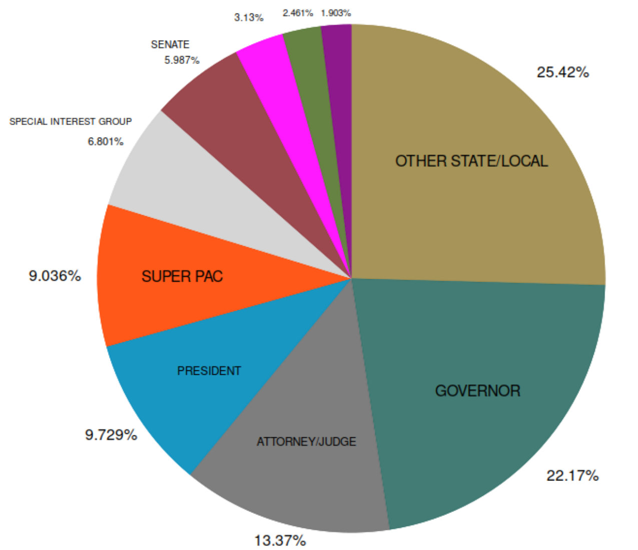
Table 3: Effects on utilization and spending

	(1) Mean value	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) Elasticity
Inpatient stays (all)	1,509.56	-0.0012	-0.0012	0.0555*	0.0592**	0.060**
per 100,000 beneficiaries		(0.0021)	(0.0020)	(0.0291)	(0.0297)	(0.030)
Inpatient stays (ED)	1,002.88	-0.0009	-0.0010	0.0438*	0.0485**	0.074**
per 100,000 beneficiaries		(0.0018)	(0.0018)	(0.0236)	(0.0239)	(0.037)
Inpatient allowed amount	189.37	0.0000	0.0000	0.0061*	0.0062*	0.050*
per beneficiary ($)		(0.0004)	(0.0003)	(0.0036)	(0.0037)	(0.030)
Outpatient visits (all)	18,720.33	-0.0411	-0.0419	0.1775	0.2797	0.023
per 100,000 beneficiaries		(0.0378)	(0.0379)	(0.4570)	(0.4644)	(0.038)
Outpatient allowed amount	86.08	-0.0002	-0.0002	0.0015	0.0020	0.035
per beneficiary ($)		(0.0002)	(0.0002)	(0.0020)	(0.0020)	(0.036)
Outpatient visits (ED)	2,252.18	-0.0056	-0.0057	0.0601	0.0733	0.050
per 100,000 beneficiaries		(0.0042)	(0.0041)	(0.0418)	(0.0445)	(0.030)
ED allowed amount	9.89	0.0000	0.0000	-0.0001	0.0000	0.002
per beneficiary ($)		(0.0000)	(0.0000)	(0.0003)	(0.0003)	(0.041)
DMA fixed effects		X	X	X	X	X
Month-year fixed effects		X	X	X	X	X
Time-varying covariates			X		X	X
Observations		4,738	4,738	4,738	4,738	4,738

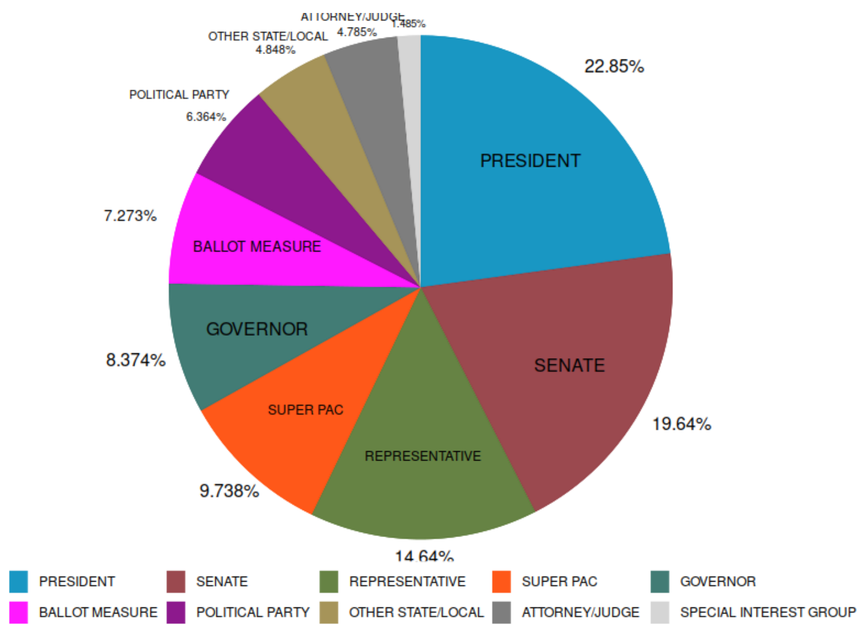
Note: The table presents the main results of the effect of advertising on use of inpatient care (rows 1–3), outpatient care (all) (rows 4-5), and outpatient care (ED visits only) (rows 6-7) by Medicare beneficiaries. The models are estimated at the DMA-year-month level, where DMA refers to designated market area, a standard definition of television ad markets. DMAs are weighted by the respective number of Medicare beneficiaries in January 2015. Column 1 presents the mean values of the respective outcomes. Columns 2 and 3 present the results using OLS models. Columns 4 and 5 present the results using 2SLS models with political advertising GRPs as the instrument for hospital advertising GRPs. Columns 2 and 4 include DMA and month-year fixed effects, while columns 3 and 5 also include time-varying market-level covariates, as listed in Section 3.2. The beneficiary-weighted mean and SD of hospital GRPs are 1,532 and 1,246, respectively. Standard errors are clustered by DMA and are presented in parentheses. Column 6 presents the elasticity of the outcome with respect to advertising implied by the IV estimates in Column 5.

A Additional figures and tables

Figure A.1: Types of Political Advertising



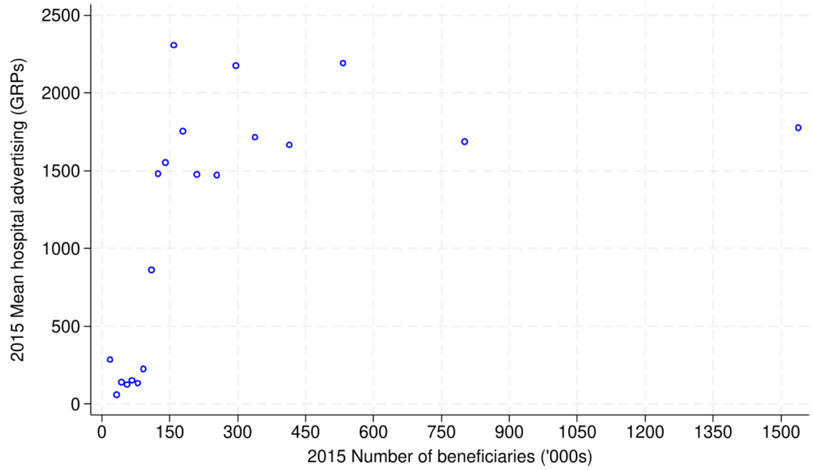
(a) 2015



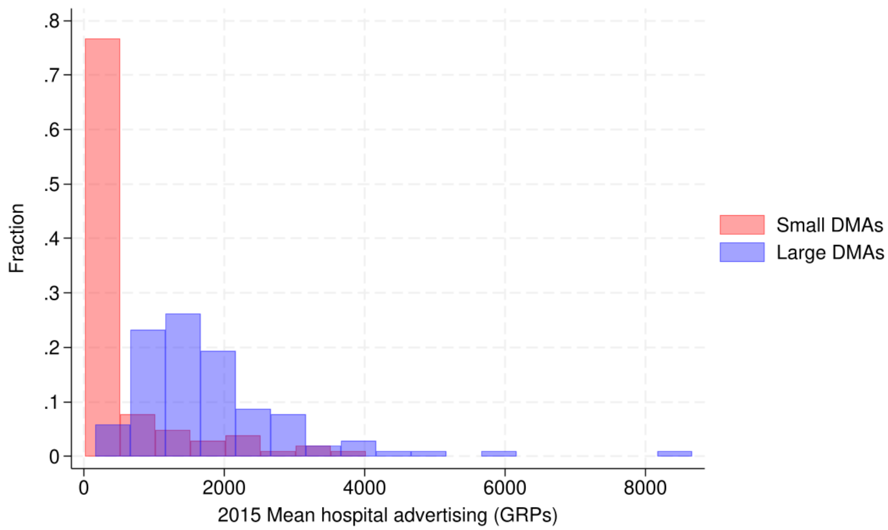
(b) 2016

Note: The figure shows the distribution of the types of political advertising in our sample. Panels (a) and (b) depict political advertising in 2015 and 2016, respectively. The values illustrated in the figures come from Nielsen Ad Intel data. Nielsen identifies what type of campaign each political advertisement describes. As seen here, political advertisements during a presidential election year are also evenly distributed between different types of races.

Figure A.2: Variation in hospital advertising by market size



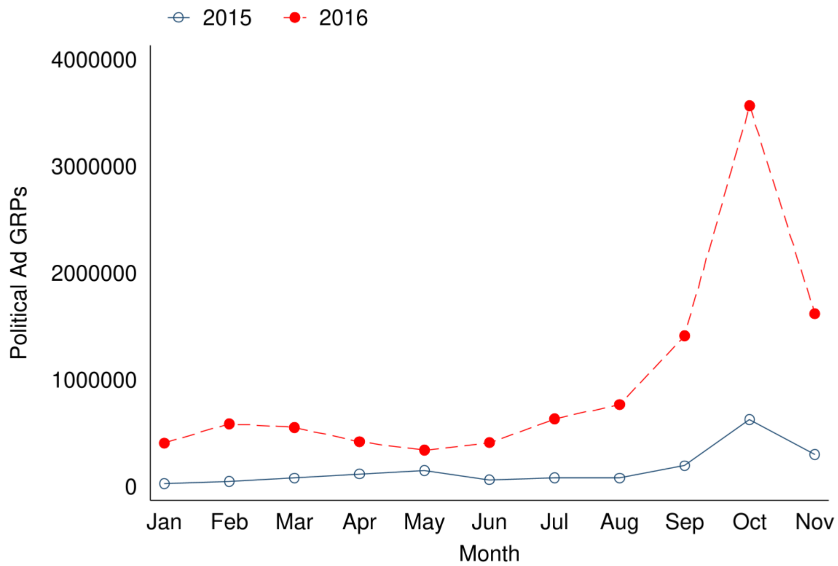
(a) Hospital advertising and market size



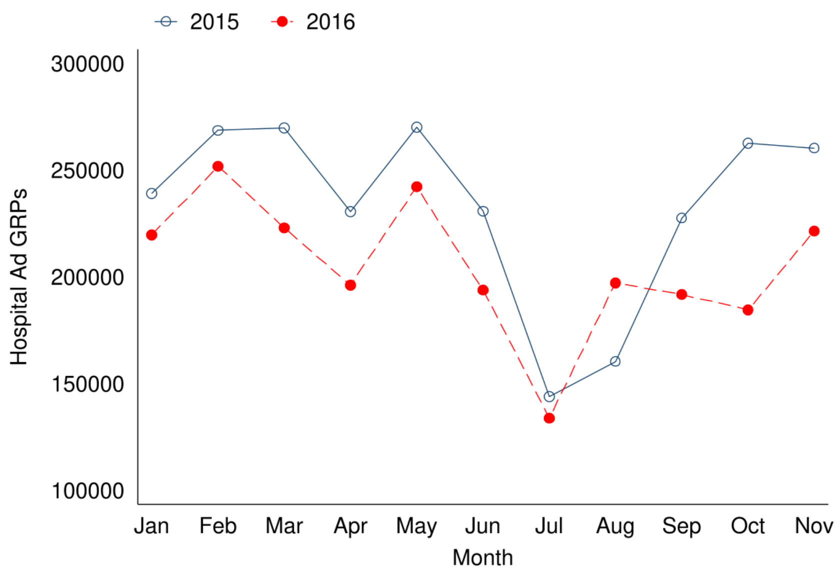
(b) Histogram of hospital advertising across markets

Note: The figure describes the variation in the level of hospital advertising on television across markets by the number of Medicare FFS beneficiaries. Panel (a) presents a binned scatter plot of the mean 2015 advertising level in GRPs on the Y-axis in 20 equal sized bins (each containing approximately 10 markets) against the corresponding mean 2015 number of beneficiaries on the X-axis. Panel (b) presents histograms of the mean 2015 hospital advertising GRPs separately for markets with below- or above-median number of beneficiaries. The median market had approximately 150,000 beneficiaries in 2015.

Figure A.3: Advertising Trends: 2015-2016



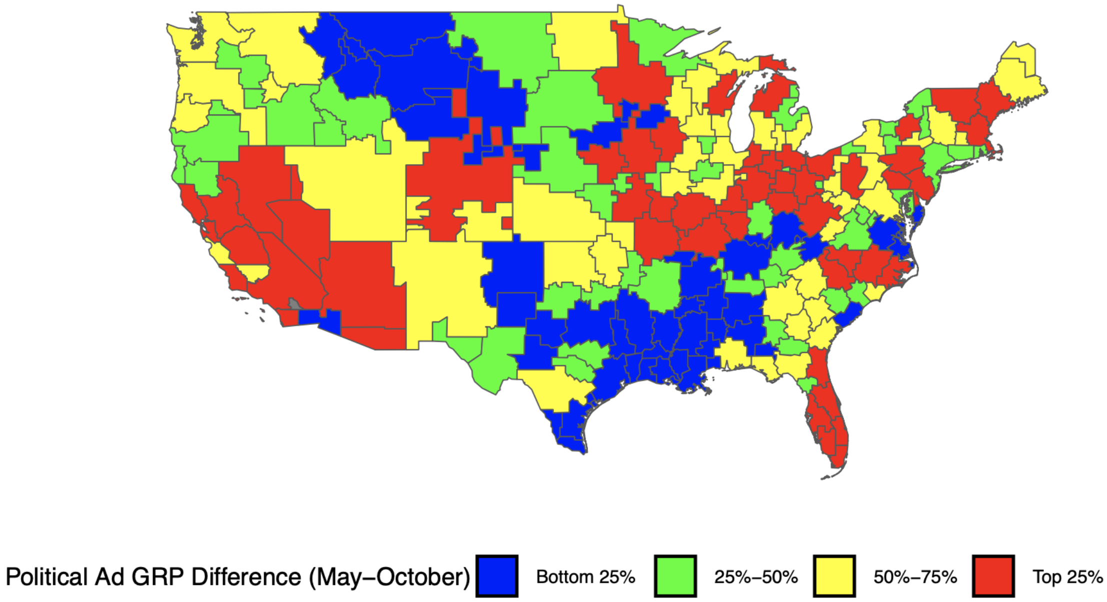
(a) Political Advertising



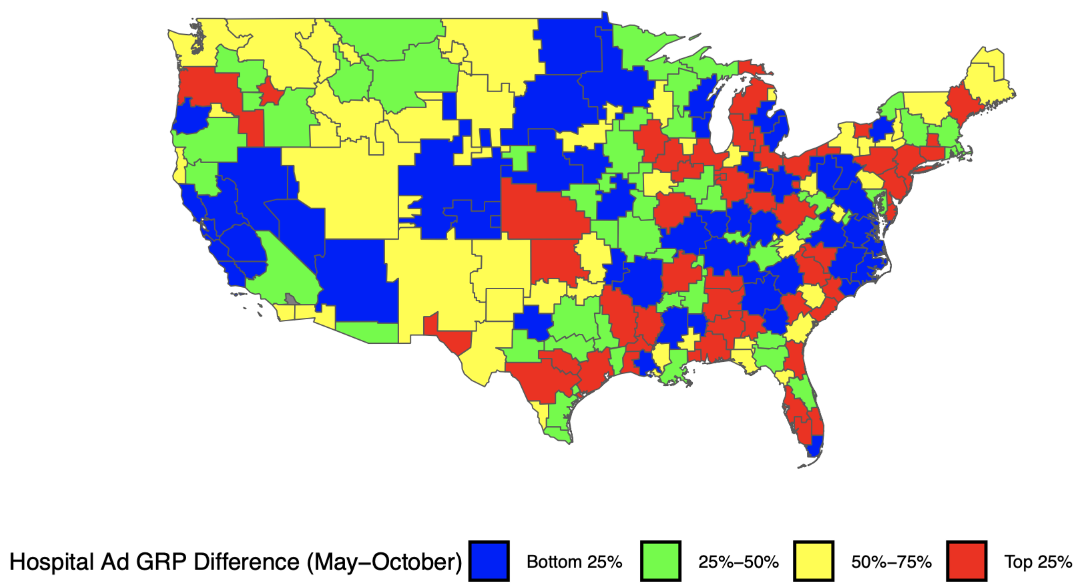
(b) Hospital Advertising

Note: The figure shows the aggregate trends in advertising across all DMAs from January through November of 2015, a nonpresidential election year, and 2016, a presidential election year. Our sample ends in November 2016. Panels (a) and (b) present the time series for political and hospital advertising, respectively. Advertising levels are expressed in gross rating points (GRPs) and are sourced from the Nielsen Ad Intel data.

Figure A.4: Change in advertising between 2015 and 2016 across markets



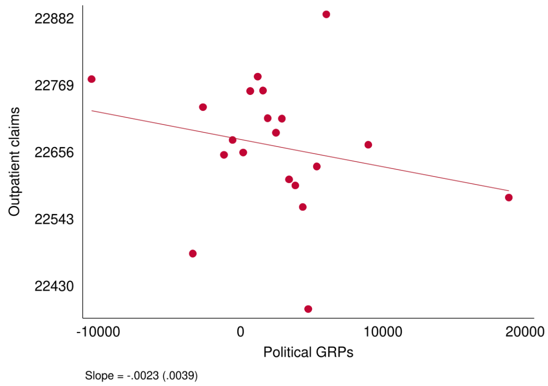
(a) Political Ads



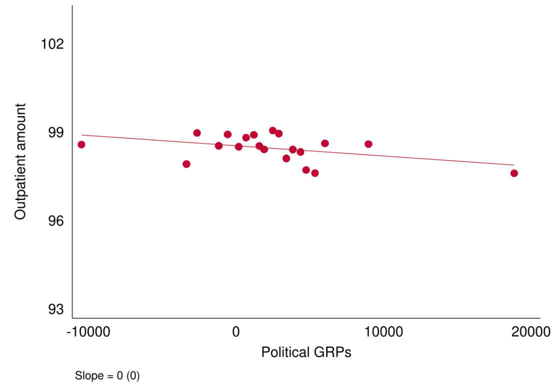
(b) Hospital Ads

Note: The figure depicts quartiles of television ad markets (DMAs) defined by the difference in mean advertising GRPs between May and October 2015, a nonpresidential election year, and May and October 2016, a presidential election year. Panels (a) and (b) present the distribution for political and hospital ads, respectively. Advertising data comes from the Nielsen Ad Intel data.

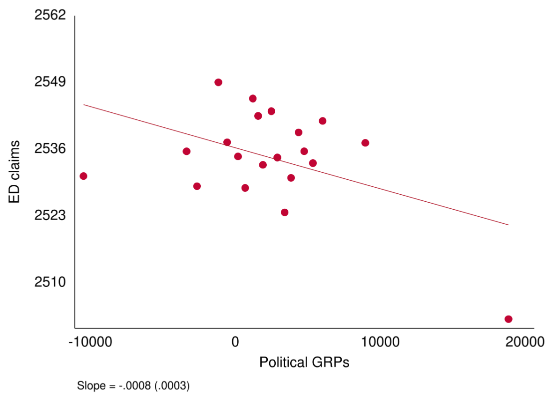
Figure A.5: Additional reduced form evidence



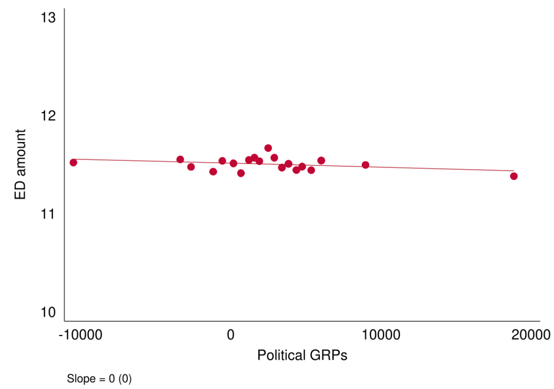
(a) Outpatient claims (all)



(b) Outpatient allowed amount



(c) Outpatient ED claims



(d) Outpatient ED allowed amount

Note: The figure presents additional binned scatter plots to visually depict the reduced form relationship between political advertising and outcomes of interest. In each plot, the dots represent mean values for 20 bins of equal numbers of DMA-month observations. We also overlay a fitted line estimated using OLS on the underlying market-level data, weighting markets by the number of FFS beneficiaries as of January 2015, and report the slope coefficient and its standard error below the plot. Each plot also presents the slope coefficient from an OLS regression using the underlying data.

Table A1: Alternate specification

	(1)	(2)	(3)	(4)	(5)
		Baseline		2-month average	
	Mean value	IV	Elasticity	IV	Elasticity
Inpatient stays (all)	1,510	0.0592**	0.060**	0.1375	0.070
per 100,000 beneficiaries		(0.0297)	(0.030)	(0.0853)	(0.043)
Inpatient stays (ED)	1,003	0.0485**	0.074**	0.1209*	0.092*
per 100,000 beneficiaries		(0.0239)	(0.037)	(0.0719)	(0.055)
Inpatient allowed amount	189	0.0062*	0.050*	0.0174	0.071
per beneficiary ($)		(0.0037)	(0.030)	(0.0108)	(0.044)
Outpatient visits (all)	18,720	0.2797	0.023	0.8101	0.033
per 100,000 beneficiaries		(0.4644)	(0.038)	(1.2668)	(0.052)
Outpatient allowed amount	86	0.0020	0.035	0.0045	0.040
per beneficiary ($)		(0.0020)	(0.036)	(0.0051)	(0.046)
Outpatient visits (ED)	2,252	0.0733	0.050	0.1594	0.054
per 100,000 beneficiaries		(0.0445)	(0.030)	(0.1113)	(0.038)
ED allowed amount	10	0.0000	0.002	-0.0002	-0.015
per beneficiary ($)		(0.0003)	(0.041)	(0.0007)	(0.051)
DMA fixed effects		X	X	X	X
Month-year fixed effects		X	X	X	X
Time-varying covariates		X	X	X	X
Observations		4,738	4,738	4,532	4,532

Note: The table presents the effects of advertising on the same outcome variables studied previously using an alternate specification. Columns 2 and 3 repeat the baseline IV coefficients and elasticity estimates, respectively, from Table 3. Columns 4 and 5 present the corresponding results from a specification in which we model outcomes as a function of the average of hospital GRPs in the current and previous month. The sample therefore drops by 206 since each DMA loses an observation. The political advertising instrument is similarly averaged. All models include DMA and month-year fixed effects and the vector of time-varying covariates. Standard errors are clustered by DMA and are presented in parentheses.

Table A2: Heterogeneous effects

	(1)	(2)	(3)	(4)	(5)
	Clinical quality			Profit status	
	High	Medium	Low	Nonprofit	For-profit
Inpatient stays (all)	0.0463	0.0538**	0.0218	0.0471**	0.0703
per 100,000 beneficiaries	(0.0295)	(0.0233)	(0.0209)	(0.0218)	(0.0565)
Inpatient stays (ED)	0.0492	0.0593*	0.0344	0.0558**	0.0675
per 100,000 beneficiaries	(0.0389)	(0.0320)	(0.0267)	(0.0256)	(0.0678)
Inpatient allowed amount	0.0381	0.0469*	0.0164	0.0363	0.0758
per beneficiary	(0.0274)	(0.0249)	(0.0233)	(0.0239)	(0.0485)
Outpatient visits (all)	0.0315	-0.0003	0.0125	-0.0098	0.1134**
per 100,000 beneficiaries	(0.0402)	(0.0283)	(0.0379)	(0.0323)	(0.0562)
Outpatient allowed amount	0.0284	0.0350	-0.0129	0.0064	0.0818*
per beneficiary	(0.0308)	(0.0314)	(0.0333)	(0.0295)	(0.0443)
Outpatient visits (ED)	0.0647**	0.0287	0.0149	0.0323	0.0886*
per 100,000 beneficiaries	(0.0321)	(0.0209)	(0.0255)	(0.0232)	(0.0465)
ED allowed amount	0.0126	-0.0319	0.0265	-0.0079	0.0195
per beneficiary	(0.0444)	(0.0332)	(0.0455)	(0.0443)	(0.0683)
DMA fixed effects	X	X	X	X	X
Month-year fixed effects	X	X	X	X	X
Time-varying covariates	X	X	X	X	X
Observations	3,749	3,749	3,749	3,174	3,174

Note: The table presents the effects of advertising on the same outcome variables studied previously but we stratify hospitals by clinical quality performance (columns 1–3) and profit status (columns 4–5). Acute care hospitals were classified as high quality if their 30-day risk-adjusted readmission rates in 2014 (sourced from CMS Hospital Compare) were in the bottom 25^{th} percentile in a given DMA and low quality if the rates were in the top 25^{th} percentile. The remaining hospitals are considered of medium quality. We restrict the sample to the 163 markets that have patient volume and spending across all three quality categories during 2015–16. The sample for the analysis by profit status is restricted to the 138 DMAs that have both nonprofit and for-profit hospitals. All models include DMA and month-year fixed effects and the vector of time-varying covariates. Standard errors are clustered by DMA and are presented in parentheses.