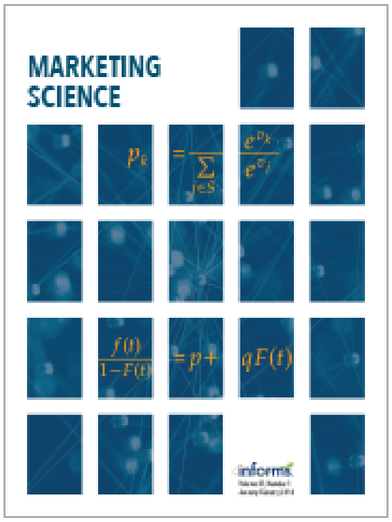

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The Impact of Hospital Advertising on Patient Demand and Health Outcomes

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Abstract. Does hospital advertising influence patient choice and health outcomes? We examine more than 220,000 individual patient-level visits over 24 months in Massachusetts to answer this question. We find that patients are positively influenced by hospital advertising; seeing a television advertisement for a given hospital makes a patient more likely to select that hospital. We also observe significant heterogeneity in patient response depending on insurance status, medical conditions, and demographic factors, like age, gender, and race. For example, patients with more restrictive forms of insurance are less sensitive to advertisements. Our demand model allows us to study the impact of a ban on hospital advertising, which has been recently considered by policy makers. We find that banning hospital advertising can hurt patient health outcomes through increased hospital readmissions. This is because hospital advertisements drive patients to higher-quality hospitals, which tend to advertise more and have lower readmission rates. However, we do not find a significant change in the overall mortality rate.

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1. Introduction

Over the last few decades, the United States has inexorably moved in the direction of a more consumer-driven healthcare society, in which greater responsibility is placed on individual patients in directing their care (e.g., see Herzlinger 2004). In particular, individual patients have increasing flexibility in choosing their care providers, and they are more likely to consider multiple factors in making their healthcare choices. For most consumer products and services, advertising plays a key role in driving consumer choice. However, in healthcare and hospital care in particular, what drives patient choice? In particular, to what extent are patients influenced by hospital marketing activities, such as advertising? Are there implications for quality of care?

The history of hospital advertising in the United States has been controversial. Before 1980, the American Medical Association (AMA) banned hospital advertising. The AMA code of ethics from 1847 considered hospital advertising to be "derogatory to the dignity of the profession, to resort to public advertisements or private cards or handbills, inviting the attention of individuals affected with particular disease" (p. 15). However, in 1980, a circuit appellate court ruled that such restraints on advertising violated the Federal Trade Commission Act protecting free commerce. Hospital advertising still continues to be a contentious topic. For example, Schenker et al. (2014) argue that hospital advertising presents significant danger of misinforming potential patients. Amid concerns that patients might be misinformed or even misled, some have discussed whether hospital advertising should be regulated in the same way that pharmaceutical advertising is regulated. There are also concerns that hospital advertising may not be the most effective use of the already limited healthcare budgets, which could be directed toward productive activities, such as capacity allocation and quality-improving process changes. In 2010, the state of Vermont considered issuing a ban on hospital advertising, citing concerns that hospital advertising was a costly drain on the state's limited healthcare budget.

Central to all of these concerns about whether hospital advertising should be curbed or the extent to which it should be regulated is the important question of whether hospital advertising is even effective. That is, are patients more likely to seek care at a hospital if they have seen its advertisements? On the one hand, unlike consumers shopping for beer or cereal, patients seeking healthcare may not make fully informed choices by themselves. In particular, physicians may still wield considerable influence in determining which hospitals patients end up visiting. On the other hand, the amount of advertising by hospitals seems to be increasing, suggesting that advertisements may not be entirely ineffective.[1] Hospital advertising has become a managerially relevant issue for hospitals that spend more than $1.5 billion a year on advertising.[2] Increased advertising could help hospitals increase their market share of patients. Given the prospective payment system in U.S. healthcare, where the bulk of the hospital's reimbursement is composed of fixed lump sum payments based on the patient's diagnosis (or diagnosis-related group), a larger volume of patients would mean a proportionate increase in revenue. The additional revenue could help defray the substantial fixed costs of operation that hospitals typically incur. However, if advertising is not effective, then given the increasing cost of healthcare in the United States, those advertising dollars could be better allocated toward other more pressing activities, such as improving care delivery. To the extent that hospital advertising steers patients toward hospitals of varying levels of quality, there are implications for the population-level quality of care.

These concerns drive our research questions. First, what is the impact of advertising on patient choice? Second, is there patient-level heterogeneity in response to advertisements? That is, are certain patient groups more responsive? Third, what is the impact of an overall ban on hospital advertising? Specifically, how does banning advertising redistribute hospital choice probabilities, and what is the impact on the resulting population-level quality of care?

To examine these questions, we assemble a novel data set that allows us to observe the hospital choice decisions across more than 220,000 individual patient visits over the 24-month period spanning September 2008 through August 2010 in the state of Massachusetts. We observe hospital-level characteristics, including hospital type, geographic location, and advertisement dollars spent. At the patient level, we obtain detailed individual-level demographic factors, including medical conditions, insurance, and zip code of residence, as well as the zip code-level U.S. median household income. To identify the effect of advertising, we use an instrumental variable (IV) approach that is unique to the television advertising market. Specifically, our identification strategy exploits the fact that hospitals tend to advertise in specific designated advertising markets (DMAs). As such, patients selecting from a given choice set of hospitals will be exposed to a particular hospital's advertising only if they happen to reside in a DMA where the hospital advertises. This leads to exogenous variation in the amount of advertising seen by patients for the different hospitals in their choice set. We combine patient choice and hospital advertising data sources to obtain a novel and comprehensive data set that includes patient-level heterogeneity and hospital heterogeneity, in which patient choice is informed by exogenous exposure to advertising.

Our empirical estimation strategy utilizes this novel microlevel data of revealed patient choice and allows us to make the following contributions. First, we are able to quantify the impact of advertising on hospital demand. To the best of our knowledge, this is the first paper to utilize individual patient-level data to estimate the influence of hospital advertising. We find that more advertising leads to a higher market share by drawing patients who reside farther away and that advertising has a persistent and prolonged effect over time.

Second, we find significant heterogeneity in the patient response to advertising across race, age, gender, income levels, type of insurance, and complexity/severity of illness. For example, individuals with more restrictive forms of insurance are less likely to be influenced by advertising. Interestingly, we observe that wealthy patients are more likely to respond to advertising. We also find that patients who live farther from a hospital are more responsive to advertising.

Third, we find that advertising has significant implications for quality of care. From the Affordable Care Act, reducing hospital readmissions has been identified as critical to improving cost and quality of hospital care. Our counterfactual results show that banning hospital advertising can negatively affect population health outcomes by increasing hospital readmissions. For example, a blanket ban on hospital advertising can lead to an additional 1.2 hospital readmissions for every 100 hospital discharges. This result is owing to the fact that, in our study setting, high-quality, low-readmission hospitals generally tend to advertise more; eliminating advertising reduces the ability of these hospitals to attract patients, thereby worsening population-level readmissions. In contrast, we do not find any statistically significant effect on mortality rate under the ban. We also find that the ban does not hurt low-income earners, although it negatively impacts high-income earners who generally tend to be more responsive to hospital advertisements.

Together, these findings further our understanding of the effectiveness of hospital advertising in driving patient choice and provide groundwork for formulating hospital-level managerial decisions as well as policy-level decisions pertaining to hospital advertising regulation.

Our paper contributes to a growing literature investigating the impact of consumer choice and market competition in the U.S. healthcare industry, including works by Luft et al. (1990), Kessler and McClellan (2000), Gaynor and Vogt (2003), Tay (2003), Howard (2005), Ho (2006, 2009), Gowrisankaran et al. (2014), and Ching et al. (2015). Recent studies (Aizawa and Kim 2018, Shapiro 2019) look at the effect of advertising in the U.S. health insurance market related to Medicare (MCR) Advantage products. Our model of patient choice is similar to that in Gaynor et al. (2016), which used revealed choice data to understand how patients select hospitals for cardiac procedures. Although many of the aforementioned studies incorporate distance between patient and hospital, none of them model advertising. Although the impact of advertising has been extensively studied in the marketing and economics literature (e.g., see Schmalensee and Genesove 2008 for a review), hospital advertising has remained relatively unexplored. Prior studies on hospital advertising (e.g., see Barro and Chu 2003, Eldenburg and Krishnan 2003) have looked at the drivers of the hospital's decision to advertise but have not studied the role of advertising in influencing individual patients. To the best of our knowledge, this is the first paper to combine hospital-level advertising data with individual patient-level revealed choice data to isolate the impact of advertising on hospital choice. In contrast to many other forms of advertising, a key distinguishing feature of hospital advertising is that the market geography (in particular, the patient travel distance) is an important driver of patient choice. For example, McGuirk and Porell (1984), Luft et al. (1990), and Sivey (2012) have shown that travel distance is a significant predictor of hospital choice. Tay (2003) and Gaynor et al. (2016) estimate the extent to which patients tradeoff quality of care for travel distance. Temporal factors (McGuirk and Porell 1984), competition (Gowrisankaran et al. 2014), patient severity (Adams et al. 1991), and socioeconomic factors (Propper et al. 2007) have also been found to moderate the role of travel distance in influencing choice of healthcare facility. We contribute to this literature by including the role of advertising in influencing patient travel distance and the overall quality of care.

The rest of the paper is organized as follows. In Section 2, we explain the hospital market and present a patient utility model. In Section 3, we describe patient-level hospital choice data and hospital-level advertising data. We also define market and patient choice sets. In Section 4, we provide reduced form evidence of hospital advertising's effect on demand. The estimation of patient choice using the utility model is described in Section 5, and the results are presented in Section 6. In Section 7, we show policy simulation results to evaluate the implications of a hospital advertisement ban, and we conclude in Section 8.

2. Model

2.1. Market Overview

We model the individual patient's choice of hospital for inpatient care as a function of their exposure to hospital television advertisement. Hospital inpatient admissions (as opposed to outpatient admissions) involve intensive treatment and invasive surgical procedures requiring at least one overnight stay. The average length of stay is 4.46 days in our data (standard deviation of 5.6 days). We focus on inpatients, because they are more likely to consider several different hospitals for their procedures and likely to be influenced by advertising over a period of deliberation. In contrast, patients seeking emergent care would be more likely to select the closest hospital rather than conduct a detailed and informed evaluation of the hospitals that they would like to visit.

Because patients generally do not travel far to seek medical care, hospital markets tend to be geographically localized around hospitals. Because counties and zip codes are drawn irrespective of hospital locations, defining markets by counties and zip codes may not be ideal. We use a commonly used definition of local hospital markets based on the hospital service area (HSA) designation. The Dartmouth Atlas Project[3] defines an HSA as "a collection of zip codes whose residents receive most of their hospitalizations from the hospitals in that area." The Dartmouth study divides the United States into more than 3,000 HSAs based on travel patterns to local hospitals.[4] In our study, we consider sets of HSAs in Massachusetts in which patients in each HSA choose from a set of hospitals in their vicinity. It is important to note that our market definition is based on patient residence, not hospital location. In other words, an HSA defines the geographic region from which patient-level demand for a common choice set of hospitals originates. This definition allows for the possibility that a hospital from that choice set is not physically located within the geographic confines of the HSA. The market selection and choice set definition are further detailed in Sections 3.1 and 3.2.

The local television advertisement market is defined at a larger geographic area called a DMA. DMAs were delineated by A. C. Nielsen in 1955, and each DMA is composed of a group of counties.[5] The DMA determines the local television stations seen by a cable or satellite television consumer, and each DMA was constructed to ensure that consumers within a DMA receive the same television content and advertising. In addition, the Federal Communications Commission takes steps to localize over the air signals to its given DMA (Shapiro 2016). In contrast to national advertising, local television advertising—which is the primary advertising channel for hospitals—can only be purchased by advertisers at the DMA level. Given that hospitals advertise in one or more DMAs at differing levels, patients across two DMAs are exposed to varying levels of advertising. In Massachusetts, there are four DMAs: Boston, Albany, Springfield, and Providence. This yields a total of three DMA borders: the Albany–Springfield border, the Springfield–Boston border, and the Providence–Boston DMA border.

In our data, we observe varying levels of hospital advertising across these borders for different hospitals across time. We provide additional discussion in Section 3.1 along with a map of DMAs in Figure 1(a).

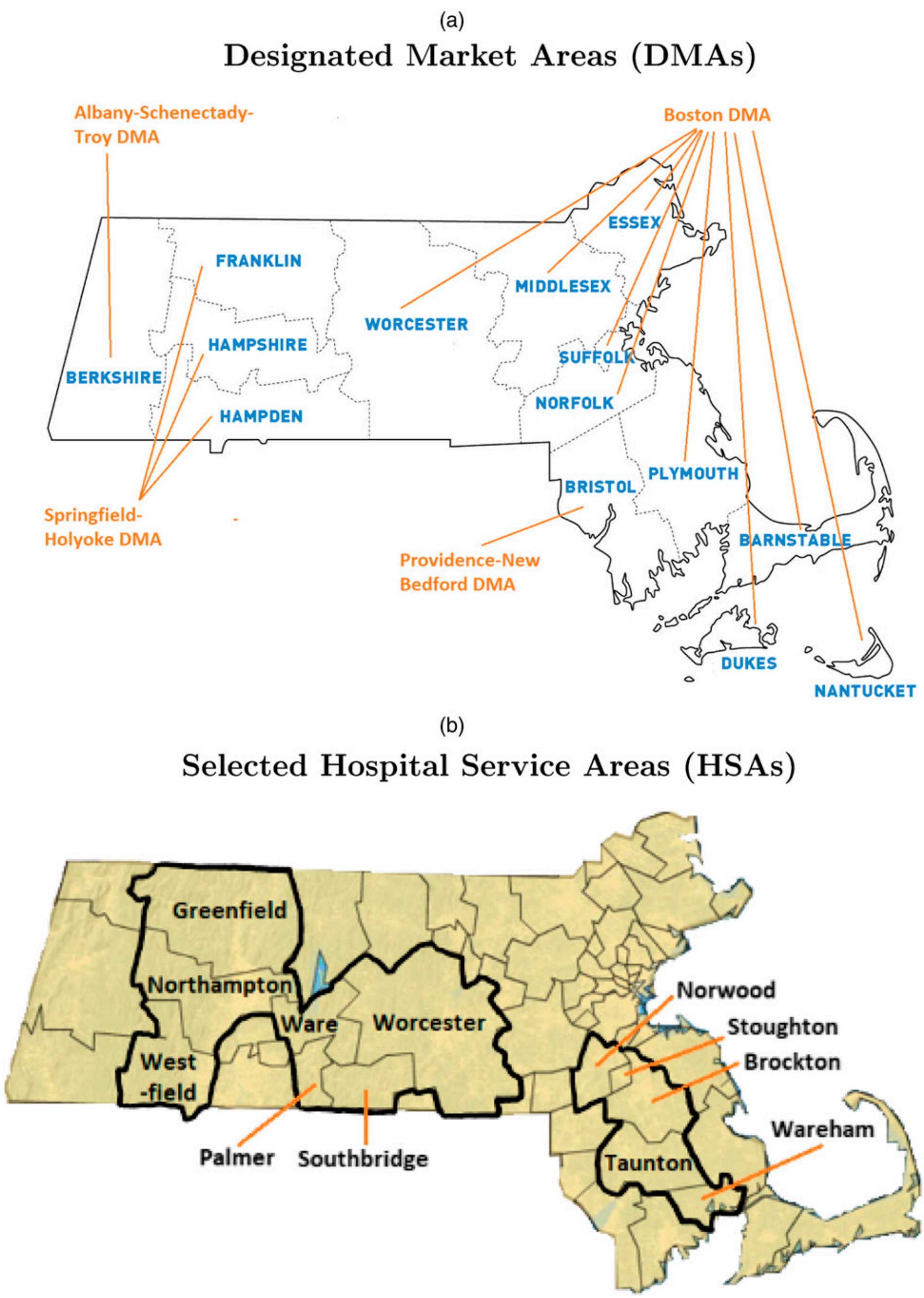
2.2. Patient Hospital Choice

We model the individual patient hospital choice in the presence of advertising after accounting for detailed patient-level heterogeneity, such as travel distance, demographic factors, insurance status, and medical conditions. Patient p who lives in market m receives the following utility from choosing hospital h in month t:

$$u_{phmt} = \alpha A_{hmt} + X_{phmt}\beta + \xi_{hmt} + \epsilon_{phmt}. \tag{1}$$

In the specification above, A_{hmt} is advertising stock, which is a function of the current period's advertisement level and the advertisement levels from previous periods. As such, A_{hmt} captures the carryover

Figure 1. (Color online) (a) DMAs and (b) HSAs in Massachusetts



Notes. We studied the 12 labeled HSAs within the bold outlines. Greenfield, Northampton, Palmer, Ware, and Westfield HSAs are in the Springfield DMA. The rest are in the Boston DMA.

effect of advertising.[6] Specifically, hospital h's advertising stock in market m in period t is defined as follows:

$$A_{hmt} = \sum_{k=0}^{K} \rho^k \log(1 + a_{hmt-k}), \tag{2}$$

where a_{hmt} is hospital h's television advertising dollars spent per 1,000 capita, and the log form reflects a decrease in the marginal effect of advertising.[7] ρ captures the rate of advertising carryover; it accounts for the "persistence" of advertising from previous periods.

Let X_{phmt} denote a set of characteristics between patients and hospitals; X_{phmt} includes a function of the distance ($Dist_{ph}$) between patient p and hospital h defined as follows:

$$f(Dist_{ph}) = Dist_{ph} + Dist_{ph}^2 + 1(Closest_{ph}). \tag{3}$$

The distance function flexibly captures the quadratic effect of distance as well as the patient's preference for the closest hospital with an indicator function that is equal to one if the hospital h is the closest hospital in patient p's choice set and zero otherwise. In addition to the distance, other patient-hospital characteristics are included in X_{phmt}. For instance, patients with severe medical conditions may prefer academic teaching hospitals (as opposed to community hospitals). Therefore, we also include an indicator function for teaching hospitals and interact it with patient medical conditions.

We account for patient preference heterogeneity by allowing coefficients α and β to vary with patient attributes $\boldsymbol{W_p}$:

$$\beta = \bar{\beta} + \boldsymbol{W_p}\beta^o.$$

The parameter $\bar{\beta}$ is the mean taste parameter, and β^o is a set of parameters representing taste variation in observed patient attributes. We include a rich set of patient attributes, such as demographic factors (age, gender, ethnicity, and income), insurance type, and medical conditions (see Section 3.3 for details). The heterogeneity coefficient for advertising stock α is similarly defined:

$$\alpha = \bar{\alpha} + \boldsymbol{W_p}\alpha^o. \tag{4}$$

The term ξ_{hmt} represents the average unobserved utility that patients in market m receive from hospital h's unobserved characteristics or quality at time t, and ϵ_{phmt} is an idiosyncratic error term, assumed to be independently and identically distributed of type I extreme value.

2.3. Endogeneity of Advertising

The term ξ_{hmt} represents hospital h's unobserved attributes that are common across patients. If advertising stock A_{hmt} is endogenously determined by some component of ξ_{hmt}, its coefficient estimate will be biased. Another potential source of endogeneity is omitted variable bias stemming from unobserved factors, such as advertisement content, advertisement in other media (radio, outdoor signs, etc.), and other forms of marketing outreach (e.g., specialists' detailing toward primary care physicians for referrals). To identify the effect of television advertisement, we use an IV approach that is unique to our setting.

To better understand the use of this instrumental variable, we first denote the mean utility portion of patient utility as δ_{hmt}:

$$\delta_{hmt} \equiv \bar{\alpha} A_{hmt} + \xi_{hmt}. \tag{5}$$

Taking advantage of our panel data structure, we can capture some of the unobserved components using dummy variables. For instance, we further model $\xi_{hmt} = \xi_h + \xi_m + \Delta\xi_{hmt}$, where ξ_h and ξ_m capture hospital- and market-specific attributes, respectively. The last term $\Delta\xi_{hmt}$ is the remaining unobserved mean utility, which is assumed to not be serially correlated.[8] There are potential endogeneity concerns stemming from unobservables $\Delta\xi_{hmt}$, such as advertising content and other marketing efforts in other channels being correlated with A_{hmt}.

To address this concern, we use an instrumental variable. Our instrumental variable is an indicator for whether the patient resides in the same DMA as hospital h after controlling for travel distance between the patient and the hospital. In the patient utility (Equation (1)), we include a flexible distance function in X_{phmt} (Equation (3)) to account for patient preference for shorter travel distance. Therefore, $\Delta\xi_{hmt}$ is the residual after controlling for distances in Equation (1) and after accounting for hospital- and market-specific attributes.

A valid instrumental variable would be correlated with A_{hmt} but uncorrelated with $\Delta\xi_{hmt}$. Hospitals tend to primarily advertise in the DMA in which they belong. There are two contributing factors to this: limited hospital marketing budget and large DMA delineations in Massachusetts. Given that hospital marketing departments have limited marketing budgets for television advertising, it is prohibitively expensive for hospitals to expand their marketing campaigns outside their DMA. We confirm this empirically in our data, finding that, with the exception of one hospital, almost all hospitals tend to advertise in their own DMA. Therefore, after controlling for distance, hospital, and market factors, patients are more likely to receive television advertisements from a hospital if they reside in the hospital's DMA.[9] However, $\Delta\xi_{hmt}$ is uncorrelated with whether the hospital happens to be in the same DMA or not. This is because the DMAs were delineated by A. C. Nielsen in 1995 for general television advertisement, and most hospitals were built many decades ago. Therefore, after accounting for distance, hospital, and market factors, we do not expect patients to form preferences based on the DMA delineation, particularly because patients are not usually even aware of DMA designations. We conduct additional analyses and provide more insights in Section 6.2.

3. Data

Our data allow us to examine and compare the hospital choices made by individuals seeking inpatient hospital care. The individuals in our sample vary in their exposure to hospital advertisements. We can determine whether a hospital advertises in a patient's market as well as the intensity of advertising (measured by per capita advertising dollars) for each hospital. Given the set of hospitals in the patient's choice set, we observe the hospital that the patient ends up visiting. We hypothesize that the greater the intensity of advertising from any given hospital, the greater the likelihood that the patient selects that specific hospital.

Our analysis is based on two primary sources of data. The first source is the complete inpatient hospital discharge data between September 2008 and August 2010 (24 months) obtained from the Massachusetts Division of Healthcare Finance and Policy. These data allow us to examine patient-level hospital choice along with a number of patient-level variables. The second source of data from Kantar Media provides us with the advertising expenditure by individual hospitals during the study period. In this section, we describe market selection, choice set construction, and various summary statistics of our data.

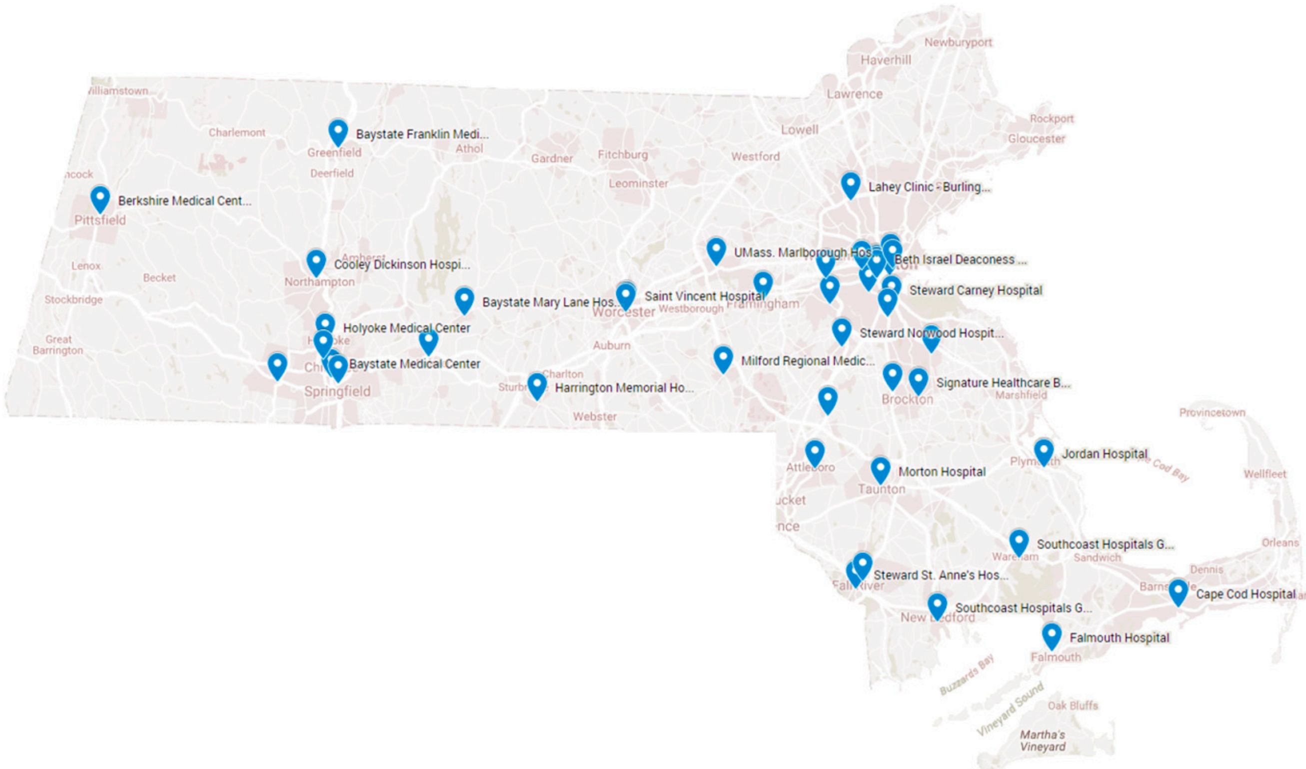
3.1. Market Selection

As previously mentioned in Section 2.1, our geographic markets for hospital care are defined by HSAs. In our study, we focus on HSAs along DMA borders for identification, mainly because our choice of IV has greater explanatory power around DMA borders. Because the variation of our IV arises from having hospitals from different DMAs in a patient choice set, an HSA at the center of a large DMA would have a weak IV problem. For instance, hospitals in Boston patients' choice sets will all be in the same Boston DMA, and there will be little variation in our IV to explain different levels of advertisement. Therefore, we limit our focus to DMA-border HSAs. For the selected HSAs around DMA borders, we use the entire set of population-level patient visit records. For our analysis, we narrow our focus to HSA × month markets with significant patient demand (more than 150 discharges) and nonzero hospital television advertisement. This results in 252 HSA × month markets in 12 HSAs, which are marked within the bold outlines in Figure 1(b).[10] Note that some HSAs (Greenfield, Ware, Southbridge, Brockton, and Taunton) are defined across two DMAs. In Greenville, Ware, and Southbridge HSAs, small rural corners with little to no demand cross into different DMAs. These small corners are excluded from analysis. These are the west corners of Greenfield and Southbridge and the east corners of Ware. Similarly, the west halves of Brockton and Taunton fall on to the Providence–New Bedford DMA. The inside hospitals in these markets do not engage in advertising, leaving no variation in advertising in the choice model. Therefore, we exclude the west parts of Brockton and Taunton from our analysis.[11] As a result, our analysis focuses on Greenfield, Northampton, Palmer, Ware, and Westfield HSAs in the Springfield DMA and the rest in the Boston DMA. From here and on, a geographical market is, therefore, defined as a, HSA in one DMA.

3.2. Choice Set

The hospital discharge data contain visit records to 72 hospitals that provide inpatient services in the state of Massachusetts. However, the assumption that every patient's choice set includes all 72 hospitals throughout the entire state is not reasonable when patients are known to be sensitive to travel distance; a patient on the west end of the state would not consider a hospital on the east end of the state. Unlike products with universal ubiquitous availability (e.g., consumer package goods and pharmaceutical products), hospital choice sets tend to be highly localized. Many hospital choice studies take advantage of variation from localized choice sets across multiple markets (e.g., Ho 2006, Raval et al. 2016). One exception would be the work of Gaynor et al. (2016), which allowed local physicians to determine coronary artery bypass grafting patients' choice sets from the full set of available hospitals in the United Kingdom. Following Raval et al. (2016), we define "inside" hospitals for each HSA to be hospitals with at least 1% market share in a given quarter. Other hospitals are then classified as the outside option. This results in 4–18 inside option hospitals for our selected HSAs, with an average of 10.5 inside hospitals. Overall, our study analyzes 43 inside option hospitals (12 teaching hospitals, including academic medical centers, and 31 community hospitals) shown in Figure 2. It is important to note that our market definition is based on patient residence, not hospital location. In other words, an HSA defines the geographic region from which patient-level demand for a common choice set of hospitals originates. This definition allows for the possibility that a hospital from that choice set is not physically located within the geographic confines of the HSA.

Figure 2. (Color online) Inside Hospitals for Analysis



Because we limit the number of inside options and categorize other fringe hospitals as the outside option, we should be concerned about skewing the substitution pattern. Fortunately, the outside option accounts for only 6% of the total observations, thereby allowing the inside options to capture most of the substitution patterns. A list of all inside option hospitals along with their characteristics can be found in Appendix A.1.

A typical outside option in marketing applications involves not buying a product. Researchers are often forced to make certain assumptions about the market size (e.g., the total potential consumption per person in the population). Such a "not buying" outside option does not apply in our context. We focus on inpatient care, which usually involves intensive medical management or invasive surgical procedures that require at least one overnight stay. Therefore, we assume that patients seek inpatient care if the need arises.[12]

3.3. Inpatient Data

We use the complete individual-level inpatient visit records from the selected 252 HSA × month markets (Section 3.1) between September 2008 and August 2010 (24 months), resulting in more than 220,000 records.[13] Instead of using all inpatient services, one may focus on a specific procedure (e.g., coronary artery bypass surgery in Gaynor et al. 2016), which makes interpretation of results straightforward. This approach, however, greatly reduces the sample size as well as external validity of our results. Therefore, we include all inpatient services for our analysis while controlling for patient medical conditions. In our analysis, we drop a small number of homeless patients, veterans, and out-of-state patients, because hospital advertising is likely irrelevant to their hospital choices.

The patient choice data identify the chosen hospital and include patient characteristics as well as the zip code of primary residence. We collect the 2010 median household income data from the U.S. Census and match them with the zip code of each patient; this allows us to obtain the median zip code-level household income for each patient. The distance between patients and hospitals is an important factor in hospital choice. We use the crow's flight distance between the centroid of the hospital's zip code and the centroid of the patient's zip code.[14] On average, patients travel 8.2 miles for inpatient care, but there is a large variance (standard deviation of 9.08 miles, with the maximum of 97 miles).

In our sample, the average age of patients is 49.5 years old, with an average median household income of about $66,860. There are 62% female patients and 18% minority patients, including 5% Hispanic and 7% African American/black.

The data also contain patient insurance types, which we divide into seven groups: MCR, Medicaid (MCD), Commonwealth (Comm), health maintenance organization (HMO), point of service (POS)/preferred provider organization (PPO), self-pay, and other commercial health insurances. Medicare is a U.S. federal program that provides health insurance to Americans ages 65 years old and older and people with disabilities. Medicaid is a U.S. Government insurance program for families and individuals who do not have the resources to obtain commercial health insurance. Commonwealth health insurance is unique to Massachusetts residents: it was created as a result of the 2006 Massachusetts healthcare reform (also known as "Romney Care"), well ahead of our study period. It is essentially healthcare insurance provided by the state government to low-income households and individuals. These three types of government insurance account for 56% of the observations.

HMOs, POSs, and PPOs are the most common types of commercial health insurances in the United States. HMO is the most restrictive form of insurance, and it typically requires a patient to have a primary care physician and obtain a referral before she can see a specialist. It also generally does not pay for out-of-network care. POS and PPO, however, provide more flexibility in patient hospital choice. HMO makes up 24% of our data, and POS and PPO account for 4%. Less than 1% of the visits are composed of self-pay patients.

Each patient record provides information on diagnoses codes based on the International Classification of Diseases, Ninth Revision, Clinical Modification, a standard that includes over 14,000 diagnosis codes and 4,900 procedure codes. We parsimoniously summarize these patients' medical conditions or diagnoses in terms of two dimensions: severity and complexity of medical condition. For severity, we use the widely used Charlson Comorbidity Index, which is a measure that predicts one-year mortality based on a total of 22 widely occurring medical conditions. The scores are generated from the patient's diagnoses codes and range from zero to six, with a higher index indicating a higher mortality prediction for given diagnoses. For instance, congestive heart failure has a score of one, whereas a liver disease has a score of five. More examples of medical conditions associated with the scores are listed in Appendix A.2. We also proxy the complexity of the patient's medical condition based on the number of diagnoses codes recorded, ranging from 1 to 15 for each patient visit. Patients with more diagnoses, hence more complications, are more likely to require complex procedures. We find the correlation coefficient of 0.56 ($p < 0.01$) between the two measures, suggesting that patients with severe conditions tend to suffer from complex diagnoses.

We detail descriptive statistics of various patient characteristics in Tables 1 and 2.

Data also include the number of days between a patient's discharge and the next hospital admission for inpatient care. Policy makers have recently focused on hospital readmission rates to help manage the cost and quality of care. We generate an indicator for whether a given patient p is readmitted to any Massachusetts hospital within 30 days of discharge; the mean probability of 30-day readmission is 12.7%. Similarly, we observe mortality during the inpatient care; the average mortality rate is 1.7%. In Section 7.2, we explore the implications of an advertising ban on patient quality of care in terms of the 30-day readmission and mortality rates.

One may wonder about the representativeness of our data sample in relation to the entire United States and whether our findings can be generalized. We collect summary statistics of 2009 national inpatient data and find them to be remarkably similar to our data in terms of variables, such as age, insurance types, length of stay, and mortality rate. This helps to mitigate concerns about the external validity of our findings. We further discuss the comparison in Appendix A.3.

3.4. Hospital Advertising Data

We combine the patient data with advertising data from Kantar Media, which track each hospital's monthly television advertising dollars within each DMA. Similar to Shapiro (2016), we scale the advertising level to dollars per 1,000 capita using county population data from the U.S. Census Bureau.

During the 24 months of study, we find that hospitals exhibit considerable variation in their level of advertising expenditure. Seventeen hospitals engage

Table 1. Inpatient Data Summary Statistics (Demographics and Ethnicity)

	Demographics			Ethnicity		
	Age	Female	Income ($1,000)	White	Hispanic	Black
Mean	49.47	0.62	66.86	0.82	0.05	0.07
Standard deviation	27.09	0.48	20.28	0.39	0.21	0.26
Min	0.00	0.00	17.47	0.00	0.00	0.00
Max	108.00	1.00	127.61	1.00	1.00	1.00

Table 2. Inpatient Data Summary Statistics (Insurance and Health Conditions)

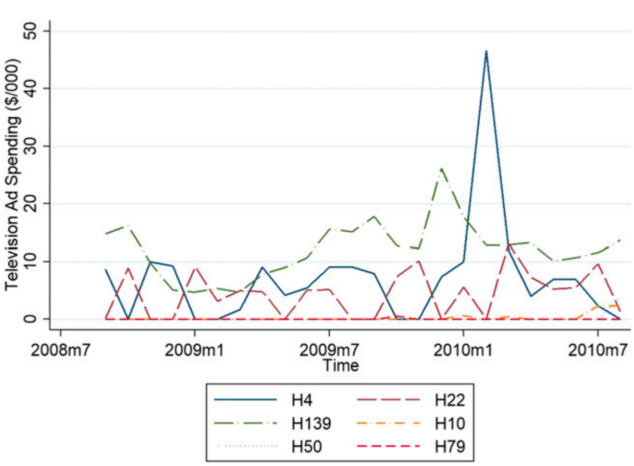
	Insurance type						Condition	
	MCR	MCD	Comm	HMO	POS/PPO	Self-pay	Charlson	Complex
Mean	0.37	0.17	0.02	0.24	0.04	0.01	0.75	6.60
Standard deviation	0.48	0.38	0.13	0.43	0.20	0.08	1.15	4.20
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	6.00	15.00

in spot television advertising. Figure 3 displays the time series of advertisement spending by a sample of hospitals that engage in television advertising. We find significant differences in the baseline spending by each hospital. On average, hospitals spend \$1.04 per 1,000 capita per month, with a standard deviation of \$3.50. We also observe diverse temporal variation in advertisement spending. For instance, hospital H22's spending varies between \$0 and \$10 per 1,000 capita, whereas hospital H139 slowly increases spending over time.

4. Reduced Form Evidence

Before estimating the structural model of individual choice, we first conduct aggregate-level analysis for empirical evidence of hospital advertising effectiveness. Note that data variation comes not only from across HSAs with different choice sets but also, from variation in advertising across different hospitals in a given choice set at a given time period. In particular, the hospitals that form the patient's choice set vary in whether they advertise to the given patient.[15] We first calculate hospital demand by aggregating the number of patients from a given HSA market m that were admitted to a given hospital h in a given month t. We then run a simple linear regression of hospital demand on the advertising dollars spent (dollars per 1,000 capita). We take the log of advertising dollars exposure, $\log(1 + a_{hmt})$, to capture the decreasing marginal effect

Figure 3. (Color online) Hospital Advertising over Time



of advertising. We report the result of this ordinary least squares (OLS) model in the second column of Table 3, and it shows that hospital television advertising is positively correlated with demand (0.222, $p < 0.01$). Model (2) of Table 3 is estimated with hospital fixed effects, and the estimate is significant and positive (0.152, $p < 0.01$). The resulting mean own elasticity, $(\partial Demand_{hmt}/\partial a_{hmt}) \cdot (a_{hmt}/Demand_{hmt})$, is 0.025.[16] In terms of the number of patients, this model predicts an increase of 10.1 patients per month for a \$1 increase in advertising per 1,000 capita.

In model (3) of Table 3, we include rivals' advertising, which has a statistically significant and negative effect on demand. This suggests a competitive effect of hospital advertisement. The last two models show that the significant and positive effect of advertisement is robust against different functional forms: model (4) of Table 3 examines a linear advertisement, and model (5) of Table 3 tests market share as an alternative dependent variable.

Collectively, these results suggest that hospital advertisement is positively correlated with demand. We next examine the individual patient choice model discussed in Section 2. The individual choice model incorporates patients' heterogeneous preferences for advertisement, travel distance, and hospital type. We also directly address the concern for the endogeneity of advertising in the main choice model.

5. Structural Estimation

Similar to Goolsbee and Petrin (2004), our estimation is performed in two steps. We first estimate the maximum likelihood function using individual patient data with product dummies δ in every market. These product dummies or fixed effects absorb the mean advertisement effect that is common across patients. We then use the dummies as the dependent variable in a second-stage regression with an instrumental variable to identify the effect of advertisement. Additional discussions on the instrumental variable and sources of endogeneity are in Section 2.3.

Denoting demand parameters $\boldsymbol{\theta} = (\alpha, \beta, \rho)$, the patient utility in Equation (1) can be rewritten in the following way:

$$u_{phmt}(\boldsymbol{\delta}, \boldsymbol{\theta}) = \delta_{hmt} + \mu_{phmt}(\boldsymbol{\theta}) + \epsilon_{phmt},$$

Table 3. Reduced Form Evidence

	Model				
	log(demand)				Market share
Dependent variable	(1)	(2)	(3)	(4)	(5)
Own advertisements $[\log(1 + a_{hmt})]$	0.222***	0.152***	0.176***		0.008**
	(0.031)	(0.040)	(0.039)		(0.003)
Rival advertisements $[\log(1 + a_{-hmt})]$			–0.147***		
			(0.024)		
Own advertisements $[a_{hmt}]$				0.016**	
				(0.007)	
Constant	3.018***	—	—	—	—
	(0.031)				
Hospital fixed effects	No	Yes	Yes	Yes	Yes
R^2	0.015	0.262	0.272	0.259	0.383
N	2,646	2,646	2,646	2,646	2,646

Note. Asymptotically robust standard errors are reported in parentheses.
$^{**}p < 0.05$; $^{***}p < 0.01$.

where $\mu_{phmt}(\boldsymbol{\theta}) \equiv A_{hmt}(\boldsymbol{W_p}\alpha^o) + X_{phmt}(\boldsymbol{W_p}\beta^o)$ is the portion of the utility that varies across patients. Conditional on mean utility δ, the probability of patient p choosing hospital h among H hospitals in a market[17] can be written as follows:

$$Pr_{phmt}(\boldsymbol{\delta}, \boldsymbol{\theta}) = \frac{exp(\delta_{hmt} + \mu_{phmt}(\boldsymbol{\theta}))}{1 + \sum_{h' \in H} exp(\delta_{h'mt} + \mu_{ph'mt}(\boldsymbol{\theta}))}. \quad (6)$$

Predicted hospital-HSA-month market shares are then obtained by aggregating individual choice probabilities over the N_{mt} patients from HSA m in month t:

$$\hat{s}_{hmt}(\boldsymbol{\delta}, \boldsymbol{\theta}) = \frac{1}{N_{mt}} \sum\nolimits_{p \in P_{mt}} \frac{exp(\delta_{hmt} + \mu_{phmt}(\boldsymbol{\theta}))}{1 + \sum_{h' \in H} exp(\delta_{h'mt} + \mu_{ph'mt}(\boldsymbol{\theta}))}.$$

In the first stage, we estimate $(\boldsymbol{\theta}, \boldsymbol{\delta})$ using the maximum likelihood function with individual patient data. Goolsbee and Petrin (2004) point out that the full product dummy approach in individual choice models creates a large number of parameter estimates.[18] With an average of 10 inside hospitals in more than 250 markets (HSA × month), we have more than 2,600 product dummies (δ) to estimate in addition to other utility parameters. This creates a significant computational burden in nonlinear demand model estimations. Berry (1994) and Berry et al. (1995) show that each unique δ can be estimated through contraction mapping. Although contraction mapping works well with relatively small data, our large data size is not suited for contraction mapping. Contraction mapping requires the computation of these individual choice probabilities for every guess of δ along the path of contraction mapping, and this significantly stymies estimation. To mitigate the above issues with contraction mapping, we use the mathematical programming with equilibrium constraints (MPEC) approach proposed by Dubé et al. (2012). We first set δ as parameters along with other demand parameters θ, and then, we apply MPEC to the demand model by estimating maximum likelihood estimation (MLE) with constraints that force predicted market shares to match observed market shares. This approach eliminates contraction mapping and hence, avoids the repeated calculation of individual choice probabilities. It also allows us to utilize state-of-the-art optimization solvers.[19]

We reframe the approach from Dubé et al. (2012) for MLE of individual choice probabilities as the following optimization problem:

$$\max_{\boldsymbol{\theta}, \delta} \sum_{p=1}^{P} \sum_{h=1}^{H} \sum_{t=1}^{T} d_{phmt} \log\left[Pr_{phmt}(\boldsymbol{\theta}, \delta)\right]$$

$$\text{subject to } \hat{s}_{hmt}(\boldsymbol{\theta}, \delta_{hmt}) = S_{hmt} \quad \forall h \times m \times t,$$

where $s(\boldsymbol{\delta}; \boldsymbol{\theta})$ is predicted market shares, S_{hmt} is observed market shares, and d_{pht} is an indicator function that takes a value of one if patient p chose hospital h and zero otherwise.

In the second stage of estimation, we use the recovered δ_{hmt} to estimate the mean advertising effect in Equation (5). Specifically, to address the endogeneity concern of advertisement, we run an instrumental variable regression in Section 6.2.[20] Note that ρ, along with α^o and β^o, is estimated nonlinearly in the first stage. This estimated ρ is then used to construct advertising stock regressor A_{hmt} in the second stage. Bootstrapping with resampling with draws taken from the parametric distribution of ρ shows that the standard errors are similar, and it does not change the statistical significance of results in the second-stage equation (Appendix C.3).

6. Results and Discussion

6.1. First-Stage Parameter Estimates

In Tables 4–6, we provide first-stage coefficient estimates for the effect of advertising stock and travel distance with regard to observed patient heterogeneity, such as demographics, insurance, and medical conditions.[21] For continuous patient attributes, we follow Gaynor et al. (2016) and capture the heterogeneous preference with dummy variables: for each continuous variable, we generate a dummy that is equal to one if it is greater than the mean and zero otherwise. This allows us to interpret the numerous heterogeneity results more easily.[22]

Table 4 shows that the effect of advertising varies across different patients. In general, young patients tend to be more responsive to hospital advertising. Older patients are more likely to have had prior hospital visits, and they are, therefore, more familiar with hospitals and the healthcare system in general. In contrast, younger patients, who have a lower level of familiarity with hospitals, are likely to find hospital advertising more informative. Also, higher-income earners are more sensitive to advertising. One possible explanation is that high-income earners are more health conscious and therefore, actively search for more information, thereby being more responsive to advertising. Our results also show that minority patients are more responsive to advertising than white patients.

We find that patients' response to advertisement varies with the type of insurance. Patients with government-run insurances (Medicare, Medicaid, and Commonwealth) are less responsive to advertising than patients with private insurances. This result is in line with what we found in demographics, because patients with government-run insurances tend to be older and/or lower-income patients. Patients with POS/PPO plans are significantly more responsive to advertising than patients with HMO plans (0.1327 versus 0.0479), because POS/PPO plans are more flexible in hospital choice. For instance, patients with POS/PPO plans can choose a hospital without having to see a primary care physician first, whereas most HMO plans involve seeing a primary care physician first. In other words, the advertising effect can manifest more directly for POS/PPO plan holders. Given that reimbursements from private plans are typically set higher than those under government plans, this finding suggests an additional financial benefit for hospitals to advertise, an effect similar to advantageous selection shown in Cooper and Trivedi (2012) and discussed in the work of Shapiro (2018) on Medicare Advantage advertising.

Patients' medical conditions also affect the effectiveness of advertisement. A significant positive parameter estimate on the high complexity suggests that patients with more complex diagnoses are more responsive to advertising.

We can also check to see if advertisement effectiveness is moderated by distance. For instance, are patients who live far from a hospital more responsive to advertisement? With an interaction term between advertising stock with an indicator for far distance (1 for hospitals that are farther than the

Table 4. Patient Heterogeneity on Advertising Stock

Heterogeneity	Estimate	Standard error	Significance
Demographics			
Older	−0.0514	0.0078	***
Female	−0.0021	0.0050	
High income	0.0138	0.0070	**
Hispanic	0.1226	0.0169	***
Black	0.1350	0.0157	***
Other ethnicity	0.0309	0.0118	***
Insurance			
Medicare	−0.0377	0.0086	***
Medicaid	−0.0312	0.0091	***
Commonwealth	−0.0577	0.0199	***
HMO	0.0479	0.0084	***
POS/PPO	0.1327	0.0170	***
Self-pay	−0.0061	0.0299	
Medical conditions			
High Charlson Comorbidity Index	0.0072	0.0067	
High complexity	0.0601	0.0082	***
Other			
Farther distance	0.0639	0.0096	***
Advertisement carryover (ρ)	0.5299	0.0615	***

Note. The reference ethnicity is white, and the reference insurance is other commercial health insurance.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5. Patient Heterogeneity—Distance

Heterogeneity	Estimate	Standard error	Significance
Distance function			
Closest	0.1246	0.0111	***
Distance	−19.2647	0.2486	***
Distance^2	15.8690	0.4172	***
Demographics			
Older	−0.4782	0.0792	***
Female	−1.3167	0.0648	***
High income	−0.1417	0.0844	*
Hispanic	−0.3078	0.1825	*
Black	1.1288	0.1659	***
Other ethnicity	0.0576	0.1543	
Insurance			
Medicare	−3.2212	0.0958	***
Medicaid	−2.4323	0.1195	***
Commonwealth	−0.8455	0.2398	***
HMO	−0.4399	0.0956	***
POS/PPO	0.7789	0.1573	***
Self-pay	−1.8525	0.4206	***
Medical conditions			
High Charlson Comorbidity Index	1.4003	0.0900	***
High complexity	−1.0851	0.0845	***
Seasonality			
Winter	−1.5708	0.3342	***
Summer	−0.6477	0.2849	**

Note. The reference ethnicity is white, and the reference insurance is other commercial health insurance.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

average), we find that patients who live far from a hospital are more responsive (0.0639, $p < 0.01$). Ackerberg (2001) postulates that, although both experienced and inexperienced customers are "relatively equally" impacted by prestige effects of advertising, inexperienced customers are more affected by the informative effects of advertising. Therefore, our result is consistent with the presence of informative advertising.[23]

We also estimate the advertising carryover rate (ρ) of 0.53, which implies that 53% of advertising stock carries over from one month to another. With this decay rate, the impact of advertising falls below 10% after four months. Our monthly rate is lower than what Dubé et al. (2005) found (0.656 monthly or 0.9 weekly) for frozen entrée product advertising. Relative to the findings of Shapiro (2016) with antidepressant drug advertising in the United States, our carryover rate is lower than the category-level persistence of the drug advertising (0.68 monthly) but higher than the product-level persistence of 0.32. We tested with different lengths of lags in the advertising stock (e.g., five months instead of four months) and obtained a very similar carryover rate.[24]

Next, we examine parameter estimates of travel distance in Table 5. The first three are the mean parameter estimates for distance function (Equation (3)). The significant and positive (negative) estimate on the closest hospital (linear distance) implies patients' disutility for traveling to distant hospitals. The significant and negative estimate on the squared distance suggests a decreasing marginal disutility for travel distance.

To examine heterogeneous preferences for distance, we interact the linear distance terms with patient attributes. For instance, we find that older female patients prefer proximate hospitals. A positive estimate on the Charlson Comorbidity Index signifies that patients with more severe medical conditions are willing to travel to farther hospitals, whereas patients with more complex diagnoses do not travel far. This is because a higher level of severity means a greater likelihood of an adverse outcome, meaning that patients are more likely to seek higher quality of care, even if it means traveling farther. Complexity, however, has to do with having multiple conditions. In particular, patients who are seeing multiple specialists for their care on a regular basis are more likely to want to be closer to the other care providers, and this could explain their desire to travel less. We also explore seasonal differences in preference for travel distance. We capture the seasonality by interacting

Table 6. Other Interaction Terms

	Estimate	Standard error	Significance
Teaching × high Charlson Comorbidity Index	0.1971	0.0217	***
Teaching × high complexity	0.1056	0.0198	***

***$p < 0.01$.

travel distance with a winter dummy (December to February) and a summer dummy (June to August). We find that patients are the most (least) sensitive to travel distance during winter (spring/fall). This is consistent with the fact that wintry conditions make travel more burdensome in New England.[25]

We also account for patients' heterogeneous preference for different types of hospitals. For instance, patients with relatively minor illnesses may not feel the need to visit a hospital offering cutting edge medical care; in contrast, high-acuity care patients might feel that they would be better served by visiting a hospital that is better equipped to handle more complex cases. Hospitals are broadly divided into two categories: teaching hospitals[26] and community hospitals. Teaching hospitals are the main training institutions for medical school residents, and they often have extensive resources for advanced medical treatments. In our model, we include interaction terms between a teaching hospital dummy and patient medical conditions to capture this substitution pattern. We find that patients with higher Charlson Comorbidity Index (i.e., more severe medical conditions) and more complex diagnoses prefer teaching hospitals (Table 6). In other words, patients with more severe medical conditions tend to seek out teaching hospitals.

6.2. Second-Stage Parameter Estimates

We now identify the mean taste parameter of advertisements ($\bar{\alpha}$) in Equation (5). We first run an OLS regression of the recovered δ_{hmt} on advertising stock A_{hmt} to check the data correlation. In column (1) of Table 7, the parameter estimate from the OLS regression is 0.167 ($p < 0.01$), suggesting that advertising increases δ_{hmt}, which in turn, increases market share.

As previously discussed in Section 2.3, a potential correlation between ξ_{hmt} and A_{hmt} can bias this estimate. We take advantage of our panel data structure and further model $\xi_{hmt} = \xi_h + \xi_m + \Delta\xi_{hmt}$, where ξ_h and ξ_m capture hospital- and market-specific attributes, respectively, that may be correlated with advertising. Hospital dummy variables (ξ_h), for example, absorb hospital types (teaching versus community hospital) or brand if a hospital is associated with a strong national umbrella brand. Market dummy variables (ξ_m) account for market-specific attributes, such as the number of competing hospitals in market m, that may affect advertising. To address potential endogeneity concerns stemming from the remaining unobserved mean utility $\Delta\xi_{hmt}$ being correlated with A_{hmt}, we use a dummy variable for the same DMA as an instrumental variable. The exclusion restriction relies on the assumption that patients do not have any preference for a hospital being in their own DMA after distance and hospital-/market-specific attributes are accounted for (see Section 2.3 for additional discussion on $\Delta\xi_{hmt}$).[27] We estimate the parameter on advertising stock to be slightly smaller at 0.133 ($p < 0.01$) in model (2) of Table 7. The first-stage regression shows a positive and statistically significant relationship between advertising and the instrumental variable along with the first-stage partial F statistic of 51.56. In model (3) of Table 7, we further include time dummy variables (ξ_t) to address additional endogeneity concerns owing to seasonality. For instance, weather conditions in Massachusetts can affect potential patients' unobserved health or proclivity to travel, which can then affect hospital advertising.[28] We capture these effects through time dummy variables. Model (3) of Table 7 results in a lower advertising stock estimate (0.104, $p <$ 0.01). This is a preferred model, because it addresses advertising endogeneity with an instrumental variable after accounting for hospital-, market-, and time-specific attributes, and the Hausman test shows that it is significantly lower than the OLS estimate (p = 0.013).[29] Our subsequent analyses are based on the conservative model (3) of Table 7 estimates. To additionally control for market-time unobservables that

Table 7. Second-Stage Estimates

	Model and regression			
	(1) OLS	(2) IV1	(3) IV2	(4) IV3
Advertisement stock	0.167***	0.133***	0.104***	0.134***
	(0.021)	(0.042)	(0.033)	(0.036)
Constant	3.187***	—	—	
	(0.037)			
R^2	0.022	—	—	
N	2,261	2,261	2,261	2,261

Notes. Instrumental variable regressions include hospital and market dummy variables. Model (3) additionally includes time dummy variables, and model (4) adds market × quarter dummies as well. Asymptotically robust standard errors are reported in parentheses.

***$p < 0.01$.

affect hospital advertising, we included market-quarter fixed effects in model (4) of Table 7, which did not yield significantly different results from model (3) of Table 7.

6.3. Results Discussion

The second-stage estimate on television advertising stock implies a positive relationship between television advertising exposure and hospital choice. From our recovered estimates of the advertisement parameters, we can now calculate short-run own elasticity of the current period advertising a_{hmt} with respect to hospital market shares s_{hmt}. We calculate$(\partial s_{hmt}/\partial a_{hmt}) \cdot (a_{hmt}/s_{hmt})$ and find the average short-run own elasticity of 0.023, which is close to the lower end of other health-related product elasticities: Shapiro (2016) finds short-run elasticities of 0.018–0.037 for antidepressant drugs, and Tuchman (2018) measures them to be 0.08–0.16 for e-cigarette advertising.[30] The elasticity varies across different groups of patients, and we further examine this variation by calculating choice probability elasticity $(\partial P_{phmt}/\partial a_{hmt}) \cdot (a_{hmt}/P_{phmt})$ for different groups of patients. For example, the least responsive group (older, white, lower-income patients with government-run insurance undergoing simpler procedures) exhibits an elasticity of 0.0068. In comparison, the most responsive group (younger, nonwhite, higher-income patients with private insurance undergoing more complex procedures) shows an elasticity of 0.045.

Although we do not explicitly model it, one consideration in interpreting the advertising effect size is hospital capacity constraint. Ching et al. (2015) found that nearly 20% of qualified Medicaid patients were rationed out because of limited supply in nursing homes. Our crude measure of utilization (equal to monthly patient traffic divided by the maximum monthly patient traffic during 2008–2010) shows an average utilization rate of 88.4%, with a standard deviation of 7.5%, suggesting that some hospitals may choose to advertise less or not at all if they are concerned about capacity constraint. In this case, our findings may be a lower bound of the advertising effect.

We can also examine the tradeoff between advertising and distance. One way is to change the advertisement dollar spent in time t and see how much distance change is needed to keep the combined utility constant (i.e., $\alpha A_{before} + \beta Dist_{before} = \alpha A_{after} + \beta Dist_{after}$). On average, hospitals are located 18 miles from patients and advertise approximately \$1 per 1,000 capita in our data. One calculation shows that, if hospitals increase their advertisement by one standard deviation (i.e., \$3.5 per 1,000 capita per month), the new marginal consumer would be approximately one mile farther away from the hospital than at the current level of advertising.

Lastly, our identification strategy depends on properly controlling for distance, because the instrument for advertising (dummy for being in the same DMA) is surely correlated with distance, which has a direct effect on hospital choice. Testing with a more flexible, cubic polynomial distance function shows that our results—in particular, the mean advertising parameter estimate—are robust (Appendix C.1).

7. Policy Simulation—Ban on Advertising

Hospital advertising is often negatively viewed for several reasons. First, there is a concern that hospital advertisements could mislead patients. For this reason, Schenker et al. (2014) argue that hospitals' direct-to-consumer advertisements should be subject to federal regulation as is the case with prescription drug advertising, which is overseen by the Food and Drug Administration. Second, some believe that advertising is an important contributor to rising healthcare costs. For example, the Vermont legislature considered a ban on hospital advertising in 2011, arguing that advertisements do not produce healthcare. Our goal here is not to support or deny these arguments. Rather, we aim to quantify the impact of hospital television advertising on patient choice; by doing so, we hope to undertake the first step toward a more informed discussion on policy formulation.

In this section, we conduct a policy simulation of a scenario in which hospital advertisement is banned. That is, we effectively "turn off" advertisement and examine the resulting change in patient choices. Ultimately, we are concerned about the expected change in the quality of care that patients receive as their hospital choice probabilities change. Although hospital quality is a multidimensional construct, we focus on two measures that are important for patient care and overall population-level health outcome: hospital readmission rate and mortality rate. The hospital readmission rate is measured by the 30-day hospital revisit rate, and the mortality rate is measured by the probability of patient death during inpatient care. The 30-day readmission rate in our data has a mean of 12.7% and a standard deviation of 0.33%. In comparison, the average mortality rate is substantially lower at 1.7%, with a standard deviation of 13%. The healthcare literature has pointed out the issue of endogeneity with respect to hospital selection bias in using these measures in an OLS setting and suggested instrumental variable solutions for identification. We use those instrumental variables to measure the impact of an advertisement ban on the overall readmission and mortality rates as well as their heterogeneous impacts.

7.1. Distance and Patient Volume

Before we examine quality of care, we look at the impact of the ban on market-level changes in two areas: patient travel distance and patient volume. Patients currently travel 8.2 miles for inpatient services on average (Table 8). If hospital television advertising is banned, our model predicts that patients choose closer hospitals, resulting in a 10.11% reduction in average travel distance. In addition, the standard deviation decreases from 9.08 to 4.47 miles. These results show that television advertising is an effective tool for hospitals to broaden their patient base and attract patients who reside farther away.

Under our counterfactual, demand is redistributed across hospitals, because there is no change in the outside option: hospitals that advertise would lose patients, and others would gain patients. If a hospital is capacity constrained, however, the counterfactual predicting a substantial patient gain may not be realistic (e.g., Ching et al. (2015) examined the impact of a limited supply in nursing homes). To address this concern, we check the magnitude of patient volume change. Under the ban, hospitals are predicted to have approximately 9.04 or fewer additional inpatients a month for 75% of the time (Table 9), which translates to roughly 1.3 extra beds required.[31] Because hospitals do not typically operate at 100% capacity and are known to have somewhat flexible capacity by sharing beds across services (in particular, across different types of inpatient beds), we assume that capacity issues can be largely avoided in most of our counterfactuals.

For a small portion of our sample, however, the predicted increase in demand may be large enough to trigger capacity concerns, which then affect interpretation of counterfactuals. If we assume that the capacity-constrained hospitals do not divert patients under our counterfactual, we may expect quality of care to decrease. If this decrease is greater than quality improvement in the hospitals that now have fewer patients, our overall quality of care prediction under advertising ban would be an underestimate. However, if the capacity-constrained hospital diverts or refers patients to other hospitals with a higher quality of care, then our results in the following sections may be an overestimate.

7.2. Hospital Readmission

Although our patient choice model predicts a market share redistribution under a ban on advertising, it does not provide us with any insight into patient health outcomes. For instance, would patients receive higher or lower quality of care as a result of the ban? We first consider a measure of quality of care that has recently gained a lot of attention among hospitals and policy makers: hospital readmission within 30 days of discharge. Potentially avoidable hospital readmissions have often been considered a sign of poor hospital quality care and have been estimated to account for \$17.4 billion of \$102.6 billion Medicare hospital payments (Jencks et al. 2009) annually. To address the growing cost of hospital readmissions, the Hospital Readmission Reduction Program was created in 2012 as part of the Affordable Care Act. The program effectively penalizes hospitals with higher than expected readmission rates by lowering their Medicare and Medicaid payments.[32] In this section, we use our model estimates to evaluate the impact of an advertisement ban on hospital readmission rates.

We start our analysis by first specifying a linear probability model of hospital readmission. We then use the model to obtain an unbiased measure of hospital quality, which we will then use in our counterfactual to determine the predicted change in population-level quality outcomes that would result under a hospital advertising ban. In our model, we regress an indicator for whether the patient p who was treated at hospital h in time t is readmitted within 30 days of discharge ($Readmission_{phmt}$) on a set of patient characteristics[33] and hospital-patient interaction terms (X_{phmt}) and on hospital fixed effects (D_h):

$$Readmission_{phmt} = X_{phmt}\gamma + D_h + \epsilon_{phmt}. \quad (7)$$

In this formulation, D_h can be interpreted as normalized readmission probability attributed to hospitals. In other words, the lower the D_h, the better the quality of care that hospital h provides. Estimating this equation by OLS, however, can result in bias estimates because of selection. For instance, the patient and her physician may decide on the hospital for inpatient service based on observed factors, such as the Charlson Comorbidity Index and distance, but also, based on unobserved (to the econometrician) severity of illness. Following Gowrisankaran and Town (1999), Geweke et al. (2003), and Gaynor et al. (2016), we instrument hospital dummies with distance to hospital $Dist_{ph}$ and indicator functions for the closest hospital. Distance to the hospital has been

Table 8. Patient Travel Distance Change

	Mean	Standard deviation	p25	Median	p75
Advertising (data)	8.21	9.08	2.10	5.40	11.80
Advertising ban (CF)	7.38	4.47	4.18	6.89	9.40
Change, %	–10.11				

Notes. Patient travel distance is averaged across patients in our sample. p25, 25th percentile; CF, counterfactual.

Table 9. Patient Volume Change

	Mean	Standard deviation	p25	Median	p75
Hospital patient volume (data)	241.27	397	44	105	225
Hospital patient volume change (CF – data)	–0.97	37.10	0.35	2.59	9.04

Notes. Patient volume figures are monthly hospital inpatient volume from the focal HSA markets. CF, counterfactual.

known to be negatively correlated with the choice of the hospital. The exclusion restriction is then valid under the assumption that such unobserved factors are identically distributed in the population, hence uncorrelated with distance to a given hospital

Models (1) and (2) of Table 10 summarize parameter estimates of Equation (7) estimated by OLS and IV regressions, respectively. The OLS results in model (1) of Table 10 suggest that many demographic characteristics affect hospital readmission. For instance, white and lower-income patients are more likely to be readmitted within 30 days of discharge. After we address selection using instrumental variables (model (2) of Table 10), however, only income and other ethnicity are significant predictors of hospital readmission. Another concern is the effect of hospital types on various medical conditions. For instance, teaching hospitals may have lower readmission rates than community hospitals for patients with more complex diagnoses. Although such hospital-patient condition interaction was a significant predictor under OLS estimation, no significance was found under IV estimation.

We found the average first-stage partial F statistics to be 714.95 (minimum of 27.46), suggesting that the IVs have enough explanatory power. Our test for endogeneity (Wu–Hausman test with a $p < 0.01$) showed

Table 10. Readmission Regression with IVs

	Model and regression			
	Readmission rate		Mortality rate	
Dependent variable	(1) OLS	(2) IV	(3) OLS	(4) IV
Demographics				
Age (00)	0.003	−0.022	0.005***	0.004
	(0.004)	(0.029)	(0.002)	(0.010)
Female	−0.012***	0.013	−0.002**	−0.005
	(0.002)	(0.015)	(0.001)	(0.005)
Income ($1,000)	−0.031***	−0.118***	0.007***	0.021
	(0.004)	(0.039)	(0.002)	(0.013)
Hispanic	−0.020***	−0.022	−0.003*	−0.005
	(0.004)	(0.017)	(0.001)	(0.006)
Black	−0.011***	−0.024	−0.004***	−0.020
	(0.003)	(0.040)	(0.001)	(0.013)
Other ethnicity	−0.033***	−0.072***	0.003**	−0.005
	(0.003)	(0.018)	(0.001)	(0.006)
Insurance				
Medicare	0.039***	0.072***	−0.001	−0.009
	(0.003)	(0.017)	(0.001)	(0.006)
Medicaid	0.034***	0.059***	−0.002*	−0.006
	(0.003)	(0.023)	(0.001)	(0.008)
Commonwealth	0.046***	0.039	−0.003	−0.015*
	(0.006)	(0.026)	(0.002)	(0.009)
HMO	0.005*	0.030***	−0.002**	−0.006
	(0.002)	(0.012)	(0.001)	(0.004)
POS/PPO	0.006	0.067***	−0.003	−0.001
	(0.004)	(0.020)	(0.002)	(0.007)
Self-pay	−0.014	−0.019	0.017***	0.002
	(0.010)	(0.032)	(0.004)	(0.011)
Medical conditions				
Charlson Comorbidity Index	0.020***	0.016**	0.007***	0.003
	(0.001)	(0.007)	(0.000)	(0.002)
Complexity	0.012***	0.025**	0.003***	0.005
	(0.000)	(0.011)	(0.000)	(0.004)
Interactions				
Teaching × Charlson	0.002	0.011	−0.002***	0.004
	(0.001)	(0.008)	(0.000)	(0.003)
Teaching × complexity	−0.001**	−0.016	0.002***	−0.006
	(0.000)	(0.020)	(0.000)	(0.007)

Note. The reference ethnicity is white, and the reference insurance is other commercial health insurances.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

that the OLS and IV estimates were statistically different from each other. Under model (1) of Table 10, 21 hospitals dummies were statistically significant at 5%. In comparison, after they were instrumented in model (2) of Table 10, 15 hospital dummies were significant. In terms of magnitude, model (2) of Table 10 produced hospital dummies with a greater variance (standard deviation of 1.12 versus 0.04 in model (1) of Table 10), suggesting that good hospitals attract sicker patients. Our finding is consistent with Gowrisankaran and Town (1999) in that the OLS estimation underestimates the distribution of quality of care, although the estimates are statistically more precise than IV estimates.

For each patient, we calculated counterfactual choice probabilities under an advertising ban using our estimated choice model. We then combined them with the estimates of D_h to calculate the expected normalized readmission probability for each patient. We compared this with observed normalized readmissions to determine how the advertising ban affects population-level overall hospital readmissions. The second column of Table 11 shows the results of this analysis. As a result of the ban, we predict a readmission rate increase of 0.0121 statistically significant at 5%. In other words, the ban increases readmission rate by 1.21 percentage points from the average 12.7%. One may wonder if the size of increased readmission rate under the ban is large enough to cause capacity issues at hospitals. Our estimated increase of readmission rate is translated into approximately 10 more readmission per HSA market per month (or 1 more readmission per hospital per HSA market per month), and therefore, we expect capacity issues to be minimal with readmissions. At the market level, 190 of 215 markets in our data experience more readmissions without hospital television advertisement. These results suggest that a blanket ban would hurt patient health outcomes through increased hospital readmissions.

7.3. Mortality

Another important health outcome measure of interest is the mortality rate (see, e.g., Gowrisankaran and Town 1999, Gaynor et al. 2016). We can easily examine the effect of the advertising ban on mortality rate by switching the dependent variable of Equation (7) to an indicator for mortality during inpatient care. With the same IVs from the previous section, we similarly compare OLS and IV regression results.

Models (3) and (4) of Table 10 summarize parameter estimates of OLS and IV regressions, respectively. The OLS results in model (3) of Table 10 suggest that many patient characteristics, such as demographics, insurance, and medical conditions, predict hospital mortality. However, after we correct selection bias using IVs (model (4) of Table 10), only one insurance type is significant at 10% in predicting mortality during inpatient care. Using a methodology similar to that done for readmissions, the OLS methodology produces more precise estimates of hospital fixed effects: in model (3) of Table 10, 14 hospitals dummies are statistically significant at 5%, whereas only 5 hospital dummies are significant under model (4) of Table 10. In terms of magnitude, model (4) of Table 10 produces hospital dummies with a greater variance (standard deviation of 0.40 versus 0.02 in model (3) of Table 10), implying that the OLS estimation underestimates the distribution of quality of care. In the previous section, we have already established that the IVs have enough explanatory power in the first stage. Our test for endogeneity (Wu–Hausman test with a $p < 0.01$) again shows that the OLS and IV estimates are statistically different from each other.

The third column of Table 11 summarizes the results of the counterfactual. As a result of the ban, we predict the mortality rate changes by 0.0001, indicating that the ban decreases mortality by 0.01 percentage points relative to the mean of 1.7%. However, this result is not statistically significant, implying that the advertisement ban has little impact on inpatient mortality rate. We also run a regression analysis of advertising ($\log(1 + a_{ht})$) on the recovered mortality quality measure FE_h and show a nonsignificant relationship, suggesting little evidence of correlation between a hospital's mortality rate and its propensity to advertise.[34]

Table 11. Normalized Quality Changes

	Readmission rate		Mortality rate	
Scenario	Current data	CF (advertisements ban)	Current data	CF (advertisements ban)
Normalized mean	–0.3293	–0.3173	0.0415	0.0414
Difference (CF – data)	0.0121		–0.0001	
95% Confidence interval	[0.010, 0.014]		[–0.0007, 0.0004]	
Markets with higher rate under CF	190/215		113/215	
Overall rate change under advertisements ban	Increases		Not significant	

Notes. The unit of analysis is the expected normalized outcome (readmission or mortality rate) per patient. The null hypothesis is that patient's observed normalized outcome and the counterfactual normalized outcome come from the same normal distributions with equal means and equal variances. The confidence intervals are around the difference of the population means. CF, counterfactual.

In summary, the effect of an advertisement ban varies across different dimensions of quality of care. The 30-day hospital readmission rate is expected to rise slightly, whereas the mortality rate is not expected to change statistically.

Lastly, we compared ξ_h (unobserved patient preference) and normalized hospital-specific readmission/mortality rates, and we did not find any relationship (correlation coefficient < 0.01, not significant), possibly because readmission and mortality data may not have been readily available to patients during our data period (2008–2010). For instance, readmission rate has only been widely discussed after the Hospital Readmission Reduction Program was created in 2012 as part of the Affordable Care Act.

7.4. Heterogeneous Effects

We find that the advertising ban can have a significant effect on the overall hospital readmission rates in our sample. We now examine concerns about the distributional effect of policies in healthcare.[35] In this section, we look at the ban's heterogeneous effect on hospital readmissions across two dimensions: income and complexity of medical condition. First, policy makers may be concerned about the advertisement ban sharply increasing readmission among low-income patients who tend to lack resources to manage their health. We ran counterfactuals of the ban separately for patients with income earnings in the top 25% (≥\$81,000) versus the bottom 25% (≤\$51,000). As Table 12 shows, the ban lowers the quality of care for the top 25% income earners: a 2.05-percentage point ($p < 0.01$) increase in readmission rate. However, the bottom 25% earners face slightly improved readmission rate (−0.2 percentage points, $p < 0.10$). Second, we also conduct a similar counterfactual based on the complexity of illness. The top 25% in terms of complexity is defined as patients with 10 or more diagnoses. The bottom 25%, however, consists of patients with three or fewer diagnoses. Table 12 shows that an advertising ban would hurt patients with higher complexity (5.1-percentage point higher readmission rate, $p < 0.01$). In contrast, the ban helps patients with less complexity, because it would lower the readmission rate by 1.68 percentage points at 1% significance. Because patients with higher income or more complex diagnoses are more sensitive to hospitals advertising (Table 4), our results are consistent with the expectation that an advertising ban would lower the quality of care for these patients through increased likelihood of readmission.

Table 12. Heterogeneous Hospital Readmission Changes (Counterfactual – Observed)

	Income	Complexity
Top 25%	0.0205***	0.0509***
Bottom 25%	−0.0020*	−0.0168***

Notes. The unit of analysis is expected normalized outcome (readmission or mortality rate) per patient. The figures are normalized quality changes (= counterfactual normalized rate – observed normalized rate). The null hypothesis is then that the patient's observed normalized outcome and the counterfactual normalized outcome come from the same normal distributions with equal means and equal variances.

*$p < 0.1$; ***$p < 0.01$.

8. Conclusion

Up until 1980, the AMA prohibited the practice of hospital advertising. Despite its relatively short existence, hospital advertising has generated considerable controversy. On the one hand, as we move toward a more consumer-driven healthcare marketplace, hospital advertising could serve as an important function in increasing awareness about products and services and help patients make more informed decisions. On the other hand, there is the potential risk of misinforming and even misleading patients. Given the large number of new entrants to the U.S. healthcare market and an increasing emphasis on patient-driven healthcare, hospitals are expected to spend more on advertising going forward.

At the heart of this controversy is the important but crucial assumption that hospital advertisements are effective. It is plausible that, because physicians wield significant influence in directing patient care and patient choice, hospital advertisements may not be particularly effective. As such, assessing whether hospital advertisements are effective is an important research question. At the very least, documenting the magnitude of the effect of advertisements could spur important policy discussions. Our work is the first paper to utilize individual-level choice data to determine the impact of hospital advertisements. We exploit exogenous variation in exposure to hospital advertisements based on the specific hospital advertising market in which the patient resides. By then examining the eventual choice of hospital, after accounting for various factors (including patient demographics, medical condition, insurance status, and travel distance), we are able to isolate the efficacy of advertisements.

Our detailed empirical analysis of over 220,000 patient visits shows that hospital advertising can be effective in driving patient choice. We find significant heterogeneity in advertisement response at the individual patient level. Specifically, older patients are less likely to be influenced by advertisements, whereas higher-income individuals are more likely to be influenced. We also find that patients who live far from a hospital are more responsive to advertisement.

Our structural model of patient choice also allows us to examine the impact of various policy scenarios.

Most notably, we consider the impact of an advertising ban on hospitals as recently considered by policy makers in the state of Vermont. We first find that an advertising ban would lead to a 10.1% reduction in average patient distance traveled. More importantly, hospital advertising has important quality of care implications. Following the Affordable Care Act, reducing hospital readmissions has been identified as important to improving cost and quality of hospital care. As a result, hospital readmissions within 30 days of discharge have been closely monitored by policy makers and government agencies. Our counterfactual results show that banning hospital advertising can negatively affect population health outcomes by increasing hospital readmissions. For example, a blanket ban on hospital advertising can lead to 1.2 additional hospital readmissions in every 100 admissions. In contrast, we do not find any statistical change in mortality rate under the ban. We also find that the ban does not hurt low-income earners; it mostly hurts high-income earners who are more responsive to hospital television advertisement.

Our results that hospital advertisements are influential in determining patient choice and health outcomes can help guide discussions on policy formulation pertaining to hospital advertising in the changing landscape for healthcare delivery. Exploring the patient choice and quality impact of advertising is a rich area of additional study, with important managerial and policy implications, particularly given the increasing role of consumer-driven healthcare in the U.S. economy. Future research could further quantify the savings generated from reduced readmissions. Under the Affordable Care Act, hospitals are financially incentivized to reduce 30-day hospital readmissions; examining the extent to which the reimbursement increase offsets the cost of advertising is managerially relevant to hospitals. Relatedly, hospitals often have constrained budgets that need to be allocated across competing activities, such as patient flow improvement, capacity allocation, or technology investments. A supply-side analysis comparing the merits of these activities with improving quality could further help hospitals assess the relative value of advertising.

An important driver of quality improvement is the organizational learning curve, whereby higher patient volume drives greater learning and additional quality improvement (see, e.g., Adler and Clark 1991). To the extent that advertising helps redistribute patient volume across hospitals, over time we can expect to see additional quality improvements at the hospitals that draw larger patient populations. Understanding the volume redistribution and long-term hospital quality owing to advertising could be an interesting area of additional study. Although our analysis accounted for patient complexity and severity, there could be other unobserved characteristics of patient health status, which would affect the interpretation of our counterfactual results. For instance, because of the unobserved severity of sickness in data and the possible heterogeneity in the response to advertising, hospitals that used to get healthier patients may now get sicker patients after advertising is banned. Consequently, the readmission rate can actually increase among these hospitals. A model with more individual patient health data could addresses these concerns and strengthen the policy implications.

In addition, physicians may also play a role in influencing patient choice of hospital. We assume that all patients who live in the same DMA receive the same advertising exposure, and consequently, we estimate the population-averaged effects. Future research could examine this effect with more granularity at the individual level and based on the time and attention paid by specific patients to the displayed advertisements. Finally, our analysis is based on data from a single state. Although we find that our patient population is similar to the national average, there might be idiosyncratic differences across geographic regions. Understanding these additional factors could be an area for future research.

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Appendix A. Data

A.1. List of Inside Hospitals and Characteristics (Table A.1)

Table A.1. Inside Option Hospitals

Hospital	DMA	Market share	Advertisements ($/000)	Readmit	Mortality
1	Springfield	0.29	3.42	0.10	0.01
2	Springfield	0.16	1.11	0.09	0.01
3	Springfield	0.24	7.11	0.09	0.02
4	Albany	0.01	0.00	0.14	0.01
5	Boston	0.02	0.00	0.14	0.02
6	Boston	0.05	0.24	0.09	0.01
7	Boston	0.03	3.16	0.13	0.02
8	Boston	0.04	4.45	0.13	0.02
9	Boston	0.01	0.00	0.10	0.00
10	Springfield	0.22	0.16	0.12	0.02
11	Boston	0.02	0.00	0.08	0.00
12	Boston	0.03	0.00	0.14	0.01
13	Boston	0.24	0.00	0.11	0.01
14	Springfield	0.02	0.00	0.12	0.02
15	Boston	0.08	0.02	0.12	0.01
16	Boston	0.01	0.00	0.00	0.17
17	Boston	0.02	0.62	0.14	0.02
18	Springfield	0.03	1.50	0.12	0.00
19	Springfield	0.05	1.50	0.07	0.01
20	Boston	0.02	0.00	0.07	0.01
21	Boston	0.05	0.00	0.12	0.02
22	Boston	0.02	0.00	0.15	0.01
23	Providence	0.22	0.00	0.11	0.03
24	Boston	0.02	0.00	0.06	0.00
25	Boston	0.05	0.00	0.04	0.00
26	Springfield	0.18	1.84	0.13	0.03
27	Boston	0.15	0.06	0.13	0.02
28	Boston	0.15	0.00	0.14	0.01
29	Boston	0.06	1.16	0.08	0.01
30	Providence	0.02	0.00	0.09	0.00
31	Providence	0.06	0.00	0.12	0.02
32	Boston	0.29	0.00	0.12	0.02
33	Boston	0.01	0.00	0.18	0.01
34	Boston	0.16	0.00	0.15	0.02
35	Boston	0.01	0.00	0.10	0.00
36	Boston	0.15	0.00	0.14	0.02
37	Providence	0.01	0.00	0.00	0.00
38	Boston	0.02	0.00	0.13	0.02
39	Providence	0.01	0.00	0.09	0.01
40	Boston	0.04	1.58	0.15	0.02
41	Boston	0.02	0.00	0.15	0.01
42	Boston	0.16	0.40	0.13	0.02
43	Springfield	0.27	12.11	0.15	0.01

Notes. The reported market share is the average of a hospital monthly market share in an HSA market. Because a given hospital can be available as an inside option in multiple neighboring HSAs, the sum of market shares exceeds one. The mortality rate is calculated based on all patients who visited the hospital in our sample. We found that hospital 16 has a small market share in a small market in our sample, and therefore, the mortality rate of 0.17 may not be a representative figure. Hospital 37 also had a similar issue. We reestimated the model by excluding them from the inside hospital set and obtained very similar results, because they have small demand and do not advertise. Hospital names are not disclosed following the guideline in the data use agreement.

A.2. Charlson Comorbidity Index Examples (Table A.2)

Table A.2. Examples of Charlson Comorbidity Index

Score	Conditions
1	Myocardial infarction, congestive heart failure, dementia, diabetes without end organ damage
2	Diabetes with end organ damage, leukemia, lymphoma
3	Moderate or severe liver disease
6	AIDS (not just HIV positive)

Note. AIDS, acquired immunodeficiency syndrome; HIV, human immunodeficiency virus.

A.3. Comparison with the National Inpatient Population

We collect summary statistics of 2009 national inpatient data from the Healthcare Cost and Utilization Project website (https://www.hcup-us.ahrq.gov/) to compare with our sample. Table A.3 shows that the national inpatient data are remarkably similar to our data in terms of age, insurance types, length of stay, mortality rate, etc. Our data contain more white patients, because we focus on rural areas of Massachusetts. Also, Massachusetts has fewer self-pay patients, because it expanded Medicaid coverage through so-called Romney Care before our data period.

Table A.3. National Data vs. Our Sample

	National inpatient		Our sample	
	Mean	Standard deviation	Mean	Standard deviation
Age, years	48.19	27.78	49.47	27.09
Female	0.58	0.49	0.62	0.48
Number of diagnoses	7.71	5.11	6.60	4.20
Medicare	0.37	N/A	0.37	0.48
Medicaid	0.20	N/A	0.17	0.38
Self-pay	0.06	N/A	0.01	0.08
White	0.56	N/A	0.82	0.39
Black	0.12	N/A	0.07	0.26
Hispanic	0.11	N/A	0.05	0.21
LOS	4.58	6.74	4.46	5.60
Mortality rate	0.02	0.14	0.02	0.13

Note. LOS, length of stay.

A.4. Data Variation

In this section, we check the source of data variation by regressing the aggregate demand from Section 4 on fixed effects. Including market fixed effects results in an R^2 of 0.23, suggesting that there is substantial variation across markets. Adding hospital fixed effects almost doubles the R^2. Allowing the hospital fixed effects to vary across time marginally increases R^2 by 0.035. In summary, most data variation arises from hospital and market variation. Our IV takes advantage of this hospital × market variation after controlling for distance-related variation.

At the market level, 32.5% of considered hospitals are in different DMAs in our border sample regions, and less than 3% of patients end up choosing hospitals outside their home DMA (Table A.4).

Table A.4. Data Variation

Variables included	(1)	(2)	(3)
Market (HSA) FE	Yes	Yes	Yes
Hospital FE	No	Yes	Yes
Hospital × Time FE	No	No	Yes
R^2	0.233	0.496	0.531
N	2,646	2,646	2,646

Note. FE, fixed effects.

Appendix B. Clustering

In this section, we compare the standard errors under different assumptions on the variance-covariance error structure. First, model (3) of Table 7 is reproduced in column (1) of Table B.1 with heteroskedasticity robust standard errors. The most appropriate assumption on the variance-covariance error structure would be to allow the unobserved errors to be correlated across competing hospitals as well as across time in a given market. Therefore, in column (2) of Table B.1, we report the standard error clustered at market level, which is found to be slightly higher than the heteroskedasticity robust error. However, as Cameron and Miller (2015) note, the asymptotics of clustering require the number of clusters to go to infinity. Unfortunately, we only have 12 markets (HSAs) at which we can cluster in our data sample, making us question the consistency of clustered standard errors. Because standard errors do not differ much, we report heteroskedasticity robust standard errors that are consistent, although there are stronger assumptions on the variance-varicose matrix of the error terms.

Table B.1. Clustering

	(1)	(2)
Advertisement stock	0.104*** (0.033)	0.104*** (0.038)
N	2,261	2,261
Standard error	Heteroskedasticity robust	Cluster at market

Notes. All regressions include hospital, market, and time dummies. Standard errors are reported in parentheses.
***$p < 0.01$.

Appendix C. Robustness Checks

C.1. More Flexible Distance Function

Our identification strategy depends on properly controlling for distance, because the instrument for advertising (dummy for being in the same DMA) is surely correlated with distance, which has a direct effect on hospital choice. Estimating our model using more flexible cubic polynomial distance function shows that our results do not change in any significant way. In Table C.1, we only show main distance parameters for presentation purposes. The

Table C.1. Distance Functional Form Comparison

	Current model			Model with cubic distance		
Parameter	Coefficient	Standard error	Significance	Coefficient	Standard error	Significance
Closest	0.125	0.011	***	0.103	0.011	***
Distance	−19.265	0.249	***	−20.883	0.305	***
Distance^2	15.869	0.417	***	24.563	1.104	***
Distance^3				−8.205	1.010	***
Mean advertisements	0.104	0.038	***	0.091	0.033	***

***$p < 0.01$.

results show that our advertising parameters are robust and are not statistically different under a more flexible model.

C.2. Model-Free Evidence of Instruments

In our data, patients incur greatly varying levels of travel distances to get to hospitals, and therefore, if we were to control for the exact distance, we would end up with a very small number of patients for such comparison. One way to circumvent this is to look at patients within rounded 10-mile distances (5–15 miles). For one hospital in Palmer HSA that advertises, among patients from the rounded 10-mile distances, about 5,000 patients are from the same DMA (e.g., exposed to advertisements), whereas 200 patients are from a different DMA (e.g., no advertisements). A two-sample t test shows that patients from the same DMA are significantly more likely to choose the hospital (18.9% versus 1.0%, $p < 0.01$).

Appendix C.3. Standard Errors from Carryover Estimation

Using estimated carryover effect (ρ) to construct the advertising stock regressor in the second stage can be a concern for asymptotics. Therefore, we bootstrap with resampling with draws taken from the parametric distribution of ρ and compare standard errors in Table 7. Results show that the standard errors are similar, and it does not change the statistical significance of results in the second-stage equation (Table C.2).

Table C.2. Standard Error Comparison

Model	Advertisement coefficient	Robust, unadjusted	Bootstrapped, adjusted
OLS	0.167***	0.021	0.024
IV1	0.133***	0.042	0.047
IV2	0.104***	0.033	0.038

***$p < 0.01$.

Appendix D. Hospital Readmission and Mortality

D.1. Quality vs. Advertisement (Table D.1)

Table D.1. Quality vs. Advertisement

	(1)	(2)
Hospital FE (readmission)	−0.059**	
	(0.030)	
Hospital FE (mortality)		0.105
		(0.078)
Constant	0.272***	0.280***
	(0.026)	(0.026)
R^2	0.005	0.002
N	793	793

Note. FE, fixed effects.
**$p < 0.05$; ***$p < 0.01$.

Endnotes

[1] See http://www.nytimes.com/2011/09/13/business/health-care-ad-spending-rises-advertising.html.

[2] See http://www.hhnmag.com/articles/4250-advertiser-beware.

[3] See http://www.dartmouthatlas.org/.

[4] Numerous studies in the healthcare and economics literature have used HSAs as a geographic unit of study. See Fisher et al. (1992, 2000), Wennberg et al. (1996), Silverman and Skinner (2001, 2004), Dafny (2005), Carey et al. (2008), and Lewis et al. (2013) for the usage of HSAs in their studies.

[5] The HSAs are generally subsumed by the DMA. Small corners of HSAs that cross into other DMAs (e.g., Southbridge and Ware HSAs in our data) are discarded from our analyses.

[6] There is a large literature on the carryover effect of advertising, including Givon and Horsky (1990), Dekimpe and Hanssens (1995), Lodish et al. (1995), Rutz and Bucklin (2011), and Shapiro (2016).

[7] The functional form of adverting stock is similar to Dubé et al. (2005), Tuchman (2018), and Shapiro (2016).

[8] A positive serial correlation in unobserved hospital preference $\Delta\xi_{hmt}$ can overestimate our results. However, given fixed distances between patients and hospitals and controls for hospitals and markets during our two-year sample, a substantial serial correlation in unobserved hospital preference is unlikely. For instance, a dramatic increase in published hospital ranking within a two-year window is relative rare.

[9] We show some model-free evidence in Appendix C.2.

[10] Models with advertisement carryover effect allow us to include months with no contemporaneous advertisements. Although our full model incorporates carryover effects, our reduced form analysis does not. To be consistent, we focus on HSA × month with nonzero advertising.

[11] We exclude patient demand (not hospitals) from these areas.

[12] This is a common assumption in the healthcare demand literature as Gaynor et al. (2016) point out.

[13] Approximately 71% of our patients are admitted only one time, and about 6.5% of them are admitted more than three times over the course of our data. Therefore, brand loyalty or patient learning over subsequent visits is not considered in our study.

[14] We used an SAS program to calculate distances between a pair of zip codes. This can be further improved by using Google Maps API (e.g., Wang and Ching 2016 in the U.S. retail banking market), which can calculate driving distance between the exact address of the hospital and a patient zip code.

[15] We investigate sources of data variation in Appendix A.4.

[16] Because our regressor is $\log(1 + a_{hmt})$, the advertisement parameter is multiplied by $a_{hmt}/(1 + a_{hmt})$ in calculating the elasticity. Therefore, the calculated elasticity is smaller than the advertisements parameter.

[17] H is the number of inside hospitals that vary across market (HSA × month). The more accurate nomenclature would be H_{mt}.

[18] Goolsbee and Petrin (2004) estimate a probit model, whereas we estimate a logit model.

[19] We use KNITRO in our estimation.

[20] Note that we drop four initial months to construct advertising stock. The final data for estimation are, therefore, over 20 months in 12 HSAs.

[21] All standard errors in this table are calculated with analytical Hessian of MLE estimators. See Cameron and Trivedi (2005, chapter 5) for more details.

[22] Other studies, such as Gaynor et al. (2016), have used a median split.

[23] Other studies have separately measured informative role and persuasive role of pharmaceutical detailing. Ching and Ishihara (2012) used data from a comarketing agreement between pharmaceutical companies to identify those effects. Chan et al. (2013) take advantage of data on physician prescription and detailing to examine differing effects of the two mechanisms.

[24] Although advertising effects dissipate within four months, the advertisement stock model may not fully capture the long-run brand-building role of advertising. However, given that we include hospital fixed effects and market fixed effects, we believe that this issue does not impact our estimation. This is reinforced by the fact that our findings are consistent across specifications and identifying assumptions.

[25] When estimating the model without advertising, we found overall similar distance parameter estimates, except that black population's and PPO insurance holders' distance sensitivities were found to be statistically significantly overestimated.

[26] Teaching hospitals include academic medical centers.

[27] Our sample consists of patients located in the Springfield and Boston DMAs. This does not mean that hospitals in their choice sets should fall in these two DMAs. They consider hospitals in vicinity, and the hospitals are physically located in four DMAs (1 in the Albany DMA, 5 in the Providence DMA, 8 in the Springfield DMA, and the other 29 hospitals in the Boston DMA) as shown in the appendix. The mean of the same DMA instrumental variable is 0.86, with a standard deviation of 0.34 at the market level. In other words, 14% of considered hospitals are in different DMAs in our border data sample.

[28] We thank an anonymous reviewer for the suggestion.

[29] The result is robust to cluster standard error. See Appendix B for additional discussion on standard errors.

[30] For other product categories, Assmus et al. (1984) measure the advertising elasticity of sales at 0.22, and Sethuraman and Tellis (1991) show the advertising elasticity to be approximately 0.1. Ackerberg (2001) also finds the advertising elasticity of 0.15 for yogurt products.

[31] 9.04 extra patients per month × 4.46 days average length of stay/30 days in a month = 1.3 beds per month.

[32] See https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html.

[33] We include patient age, gender, race, income, insurance type, and complexity/severity of illness.

[34] We include full regression results in Appendix D.1.

[35] We thank anonymous reviewers who helped us enrich this section.

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