Does Advertising Matter to Emergency Department Patients? The Effect of Advertising on Hospital Choice, Travel Distances, and Mortality Rates

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February 27, 2023

In recent decades, the US healthcare industry has seen momentous transformations. Consumers are taking a more active role in choosing hospitals, coupled with hospitals substantially increasing spending on emergency care advertising. This is in contrast to a common belief that advertising may not be effective for patients choosing a hospital in the midst of a medical emergency, and few studies have examined the impact of such advertising. Using a dataset of individual patient choices in Florida between 2012 and 2015, we examine the effect of hospital television advertising on emergency patients' choice of hospitals and subsequent health outcomes. We find that patients are more likely to choose hospitals that advertise on television, with substantial heterogeneity across demographics and health conditions. Using the findings from our demand model, we further conduct counterfactuals—a ban on hospital advertisements. Our results suggest that hospital advertising leads to increased mortality rates. Decomposing this mortality rate change further, we show that 24% of the increase is due to increased travel distance, and the rest due to change in quality of treatment. These results suggest needs to examine the practice of hospital advertising toward emergency patients.

Keywords: hospital advertising, healthcare marketing, emergency patients, direct-to-consumer advertising

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1 Introduction

Direct-to-consumer advertising (DTCA) in the U.S. health care industry vastly grew in recent years, from $2.1 billion in 1997 to $9.6 billion in 2016 (Schwartz and Woloshin 2019). A report shows that hospital advertisements represented nearly a quarter of all health care advertisements in 2015, having increased by 41% between 2011 and 2015.[1] Such trend is in stark contrast to the traditional view of hospital advertising. Until 1980, hospital advertising was banned by the American Medical Association (AMA) which labeled it "derogatory to the dignity of the profession." The ban over overruled by a circuit appellate court in 1980 citing the violation of the Federal Trade Commission Act protecting the interest of free commerce. Although hospital advertising has been allowed since, the recent surge in marketing efforts aimed at healthcare consumers is closely related to the rise of consumerism of the U.S. healthcare sector. Healthcare "consumers" are taking a more active role—driven by high deductibles and co-payments, greater transparency of providers' quality, and an individual mandate for healthcare plans —in choosing their healthcare providers (e.g., Cordina et al. 2017; Herzlinger 2004; Huckman and Kelley 2013). Simultaneously, hospitals are increasingly counting on advertisements to attract patients.

Despite its remarkable growth, research on hospital advertising and its effect on patient choice has been scant. Kim and KC (2020b) examine individual patient choice of hospitals in Massachusetts and find that hospital advertising is effective at attracting consumers for in-patient care (i.e., intensive medical management or invasive surgical procedures that require at least one overnight stay). However, whether similar effect can be found for emergency care patients has not been studied. Studying demand for emergency department (ED) is important because ED accounts for 5-10% of the total US healthcare costs (Lee et al. 2013). One may assume that emergency patients do not have enough time to choose particular hospitals amid medical emergencies. For example, Yoon (2020) shows that the report cards on cardiac

[1] Advertising Age, https://gaia.adage.com/images/bin/pdf/KantarHCwhitepaper_complete.pdf (accessed 09-07-2022).

surgery changed elective patients' choices but did not affect emergency patients' choices of surgeons. The possibility of consumer choice for emergency care is further diminished by the fact that patients often arrive at emergency rooms in ambulances, which often take patients to the closest hospitals. However, several evidence suggest that consumer choice may play a role even in medical emergencies. US National Hospital Ambulatory Medical Care Survey in 2019 shows that only 15% of the patients used ambulances as a mode of transportation to the emergency department; Squire et al. (2010) find that approximately a half of critically ill patients do not use the ambulance, meaning that there is room for patients to select their own hospital. Even for those transported by 911 Emergency Medical Services, patient or family choice accounted for the majority (50.6%) for the selection of hospitals (Newgard et al. 2013). Furthermore, patients have more freedom to choose the hospital for ED than other medical services as the ED choice is protected by a federal law: In 1986, the U.S. Congress enacted the Emergency Medical Treatment and Liability Act (EMTALA), requiring all hospitals to provide basic medical examination and treatment to any ED patients regardless of ability to pay. Therefore, ED patient hospital choice remains an empirical question, and our study is the first attempt at examining the effect of hospital advertising on ED patient hospital choice..

If advertising were to affect ED patients' hospital choices, it may have a downstream impact on patient health outcomes. The extant literature examining patient health outcomes only focuses on how patients choose different hospitals and thereby facing different quality of treatment. However, such framework may not be sufficient when examining ED patients as the travel distance to the chosen hospital directly affects health outcomes. Suppose a critically ill patient chooses to go to a farther hospital due to advertising. It is well documented that traveling further puts an ED patient at a greater risk of fatality (Nicholl et al. 2007), i.e., risking oneself to exceed the 'golden hour'. Therefore, we develop a framework of patient health outcomes that incorporates not only the choice of the hospital but also the distance to the chosen hospital and apply it to conduct counterfactual simulations of a ban on hospital advertising.

The adequacy or necessity of hospital advertising has continuously been questioned. In the U.S., hospital advertising have been only allowed since 1980. A few decades later, in 2011, the Vermont state representative Maier introduced an act to ban hospital advertising, questioning the necessity of hospital advertising – "it's not producing health care." In fact, the U.S. and New Zealand are the only countries in the world that currently fully legalize hospital DTCA. A recent study by Ndumele et al. (2021) shows that between 2008–2016, approximately half of the acute care hospitals in the U.S. advertised, however, there is no evidence that higher-quality hospitals advertised more. Therefore, we hope to shed light on the effect of hospital advertising toward emergency patients.

We combine two data sets to investigate patient response to advertising and the resulting health outcome: individual patient discharge data and advertising data. We first assemble patient discharge data for all hospitals in Florida for the period January 2011 to September 2015, then retain the patient records that satisfy our definition of an emergency patient[2]. The patient discharge data observe approximately 64,000 emergency patients' choice of hospitals in Florida and includes detailed information on patients such as demographics, diagnoses, and an indicator for hospital mortality—patient health outcome measure in this study. We further supplement the median household income data from the 2010 US Census based on the patients' zip codes. The advertising data include information on hospital advertising expenditure, number of units, and the duration of each TV creative. We combine the two data sets using the patients' zip codes to approximate the advertising exposure of patients.

We employ a discrete-choice model to examine the effect of hospital advertising on ED patients. For identification of hospital advertising, we use an instrumental variable (IV) method used in Kim and KC (2020b) that is specific to the television advertising market, exploiting the fact that hospitals generally advertise in selected designated advertising markets (DMAs). Given this, patients are exposed to a particular hospital's advertising only

[2]We use two factors: severity and urgency. Appendix A provides the details.

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. Modeling the patient health outcome also suffers from endogeneity concerns in the quality of treatment as well as distance traveled; we address both concerns using additional IVs.

We find that advertising positively affects emergency patients' choice of hospital and that the advertising effect decreases as the hospital is located farther from the patient. A hospital that is located 20 miles from a patient would have approximately 8% less advertising effect than a hospital that is 10 miles from a patient, ceteris paribus. Furthermore, we find significant heterogeneity in patient response to advertising across age, gender, income levels, race, type of insurance, comorbidity levels (severity), and medical conditions. For instance, older and sicker patients were relatively more sensitive to advertising, and we show that the medical condition of a patient was generally the most influential in choosing a hospital.

Using the findings from our choice model, we further simulate a counterfactual policy—a ban on hospital advertisements. We find that hospital advertising leads patients to travel farther, approximately 13.5% (1.2 miles) more. Using an instrumental variable (IV) setting, we model patient's mortality rate on various factors and find that traveling 10 miles can increase one's mortality rate by 1.3 percentage points. Furthermore, we predict the average mortality rate to decrease under an advertising ban, which confirms the need to re-examine hospital advertisement policies. We further decompose this change in mortality into two factors: distance and quality of care. We find that 76% of the change in mortality is due to change in quality of care and the remaining 24% is due to change in distance.

We contribute to the literature in the following three ways. First, we specifically focus on emergency patients. Conventional wisdom is that emergency patients are not influenced by factors such as advertising and physician score cards (Yoon 2020). Few, if any, have studied the role of advertising on emergency patient's choice of hospitals even though ED patients account for up to 10% of the U.S. healthcare costs (Lee et al. 2013). To our knowledge, our study is the first to find that hospital advertising is effective among ED patients.

Second, we find significant heterogeneity within ED patient responses towards advertising. Higher income patients are relatively less sensitive to advertising, whereas the elder or patients with higher comorbidity levels are more sensitive to advertising. Furthermore, we did not find a significant difference in the advertising response between male and female patients.

Third, our approach allows us to account for the direct effect of distance traveled on mortality rates along with the indirect effect of quality of treatment. We extend the patient mortality model of Gowrisankaran and Town (1999), which is also employed in Kim and KC (2020b) to examine patient outcomes, by explicitly modeling the distance traveled by patients. The travel distance has only been used as an instrument for the endogenous hospital choices in analyses applying that model, however, our unique extension allows us to compute the effect of distance traveled on ED mortality rates. We also show that not accounting for the effect of distance traveled would substantially underestimate the impact of advertising ban.

The rest of the paper is as follows.

2 Related Literature

Our research lies in three areas of research: industrial organization in health care industry, advertising in health care markets, and patient outcome modeling.

Many of the research have focused on the impact of hospital market structure and quality on patients (see, e.g., Town and Vistnes 2001; Capps et al. 2003; Gaynor and Vogt 2003; Tay 2003; Ching et al. 2015; Gaynor et al. 2016; Ho and Lee 2017).[3] For example, Tay (2003) studies the Medicare patient (with heart-attack) responses to distance and quality differentiation, Gaynor and Vogt (2003) examine the effect of a merger simulation on prices,

[3]see also Gaynor and Town (2011), Gaynor et al. (2015), and Handel and Ho (2021) for great survey papers on industrial organization in the health care markets.

and Ho (2006); Ho and Lee (2017) focus on the welfare effects of insurer competition. We also incorporate a discrete-choice model of hospital selection, however, we turn to a slightly different direction. We focus on the effect of hospital advertising on emergency patients, which none of the preceding research has incorporated.

Town and Currim (2002)were one of the first analysis in hospital advertising. They examine hospital advertising in California from 1991 to 1997 and find that hospital advertising is positively correlated with market factors such as market concentration, the number of nearby potential patients and hospital size. Similarly, Barro and Chu (2003); Eldenburg and Krishnan (2003) study hospital advertising, however, they also focus on the supply side and not on the impact on individual patients. Though not *hospital* advertising, Aizawa and Kim (2018); Shapiro (2020) have focused on the effect of advertising in the U.S. health insurance market related to Medicare (MCR) Advantage products. Yoon and Kim (2022) show that robotic surgery advertising increases the likelihood of patients choosing robotic surgeries, with patients only responding to the relavent ad creative. Another area of related research is on the direct-to-consumer advertising (DTCA) on drugs. Previous research confirms the existence of advertising effectiveness in healthcare markets, showing that DTCA on drugs (i) is an important factor of an individual's decision to get a check-up (Hosken and Wendling 2013); (ii) increases demand for the corresponding drug (Alpert et al. 2015; Narayanan et al. 2004; Sinkinson and Starc 2019); and (iii) influences the frequency of physician visits (Iizuka and Jin 2005, 2007; Liu and Gupta 2011). Furthermore, it is found that increased erectile dysfunction drug advertising leads to a higher birth (Kim and KC 2020a). These research all show that advertising in the health care markets have an influence in some way or another.

While we were unable to find studies that connect advertising with emergency patients, many studies have examined the risk-adjusted mortality rates of emergency patients, mainly the heart-attack patients (e.g., Doyle 2011; Farsi 2004; Chua et al. 2010; Hentschker and Wübker 2020; Romley and Sood 2013; Swanson 2021; Chandra and Staiger 2007; Khwaja et al. 2011). For example, Doyle (2011) studies the variation of healthcare spending on mortality rates of heart-related patients across regions, Khwaja et al. (2011) adopts a structural model to compare the mortality rate differences of receiving catherization, and Hentschker and Wübker (2020) studies whether the use of percutaneous transluminal conary angioplasty (PTCA) is effective in reducing mortality rates for AMI patients. A potential problem in mortality regressions is the patients' self-selection (i.e., when sicker patients self-select into higher-quality hospitals), in which Gowrisankaran and Town (1999) shed light on an IV approach using differential distances. Another concern is that emergency patients typically have a golden-hour of treatment, indicating that travel distance is a crucial factor of mortality, though we did not find any studies that addressed this issue. To our understanding, our paper is the first to incorporate the direct impact of travel distance on mortality. Furthermore, we discover that omitting distance as a factor of mortality may bias other parameters such as risk-adjusted mortality rates or the "quality" of hospitals.

The study closest to our paper is Kim and KC (2020b), in which both papers focus on the effect of advertising on patient choices. We detail the differences hereinafter. First and most importantly, the patient population differs. Kim and KC (2020b) studies the effect of advertising on general inpatients, whereas we specifically focus on emergency patients. Second, the geographical region and time periods differ. They use patients in Massachusetts for the period September 2008–August 2010, whereas our data comes from Florida. Our study period is also relatively newer and longer (January 2012 – September 2015).Third is the estimation procedure. They use GMM method to control for endogeneity of advertising and thereby having two-stages of estimation process. We adopt a control function approach, which we find to be much more computationally feasible while achieving the same objective. Last, our patient outcome model accounts for travel distance, which is an essential component in mortality prediction of an ED patient.[4] In contrast, for general patients seeking hospitals, travel distance would generally not influence their chance of fatality and thus why is not needed for the inpatient population in Kim and KC (2020b).

[4]see Section 7.2 for the details.

3 Data

We primarily use two data sets: emergency patient discharge data from Healthcare Cost and Utilization Project (HCUP) and hospital TV advertising data from Kantar Media. We first discuss the patient data. Then, we explain the definition of an emergency patient. Lastly, we describe the advertising data.

3.1 Patient Data

The emergency patient data set records every patient's discharge data on a quarterly basis for the period January 2012 to September 2015 in Florida. This data set comprises detailed patient demographics and clinical information, and hospital characteristics such as hospital location and hospital brand. We use the hospital location and patients' zip codes to derive the distance between the two based on the car route (HERE API).[5] In addition, we supplement the median household income data from the 2010 US Census based on the patients' zip codes.

We focus on patients that are emergency patients. [6]We use two conditions to identify an emergency patient: severity and urgency. For severity, we base it on the mortality rate, and for urgency, we additionally take into account the patient's length of stay in hospitals. Further details and the list of diagnosis classifications are in Appendix A. Our final sample leaves us with approximately 64,000 patients across 355 markets (HSA-quarter level).

Table 1 details the descriptive statistics of the data. Patients' mean (median) travel distance to hospitals is 10.03 (7.52) miles. Approximately 41.5% of the patients are female. The mean (median) median household income and age is 47,780 (45,000) dollars and 65 (68), respectively. The average number of comorbidities[7] (an index for health severity) is 2.75.

[5]https://developer.here.com/documentation/routing-api/dev_guide/index.html provides more information on HERE Routing API.

[6]Hereinafter we use the terms "emergency patient" and "patient" interchangeably.

[7] We use the Elixhauser comorbidity index (Elixhauser et al. 1998), which tracks the presence of 31

The department notes the department of the hospital the patient visited, i.e., classification of patients' primary diagnosis. Cardiac-related diagnoses are the most common, representing 37.4% of the sample. Renal-related diagnoses were the least common, representing about 8.6%. Regarding race, 80% of the patients are white, 8.7% are black and 8.1% are Hispanic. The "other" races account for 3.1%. Medicare insured patients account for over half (57.8%) of the patients, followed by private insured patients (21.1%).

Table 1: Patient Data Summary Statistics

	Demographics and Characterstics					Ethnicity			
	Age	Female	Income ($1,000)	Distance	Comorbidity	White	Hispanic	Black	Other
Mean	64.7564	0.4152	47.7792	10.0317	2.747	0.0809	0.0868	0.8013	0.031
Std. Dev.	20.6158	0.4928	13.3642	7.6324	2.2201	0.2727	0.2815	0.399	0.1734
Min.	0	0	9.979	0.3523	0	0	0	0	0
Median	68	0	45.003	7.5198	2	0	0	1	0
Max.	114	1	111.094	48.6732	13	1	1	1	1

	Insurance type				Department			
	Medicare	Medicaid	Private	Other	Brain	Pulmonary	Cardiac	Renal
Mean	0.578	0.0699	0.2106	0.1415	0.3195	0.0803	0.3736	0.0857
Std. Dev.	0.4939	0.255	0.4078	0.3486	0.4663	0.2717	0.4838	0.2799
Min.	0	0	0	0	0	0	0	0
Median	1	0	0	0	0	0	0	0
Max.	1	1	1	1	1	1	1	1

diagnoses (e.g., cardiac arrhythmias, hypertension, diabetes, metastatic cancer, obesity) in patients.

3.2 Advertising Data

The advertising data is from Kantar Media. This data set includes hospital-DMA-month level advertising expenditure, number of units, and the duration of each TV creative. We first aggregate the advertising data into quarterly level to match our emergency patient data and then combine the two data sets using the hospital identifiers and patients' zip codes. Over the whole sample period, we have 87 unique hospitals, of which 57 (65.5%) hospitals had advertised. Furthermore, all the hospitals except for one advertise inside their DMA[8] only.

For advertising expenditures, the summary statistics are shown for positive figures, which are in dollars per 100 capita and are based on hospital-HSA-quarter observations. Out of the 1,018 hospital-HSA-quarter observations, 429 are positive. The mean (median) advertising dollars (per 100 capita) is $0.78 ($0.24). There is a large variance in hospital's advertising expenditure, with a standard deviation of 1.37 and a minimum (maximum) of near 0 (10.87).

Table 2: Advertising Summary Statistics

Variable	Mean	Std. Dev.	Min.	25%	50%	75%	Max.
Ad ($/100 capita)	0.7807	1.3679	0.0006	0.0198	0.2449	1.0939	10.8686

Note: Statistics are shown for positive figures, which are in dollars per 100 capita and are based on hospital-HSA-quarter observations.

[8] A Designated Market Area (DMA) is defined by Nielson Media and is a collection of zip codes used for advertising purchases.

4 Model

The outline of the model is as follows. In a given quarter t and a market (Hospital Service Area; HSA) h, patient i visits one of the J_{ht} (differentiated) hospitals, $j = 1, \ldots, J_t$, or the "outside" hospital $j = 0$. Following Raval et al. (2016); Kim and KC (2020b), inside hospitals are those with at least a one percent market share in a given HSA biannually. The hospitals below this threshold are grouped as outside hospitals in their respective HSA-quarter. The utility of consumer i visiting hospital h in HSA m in quarter t is

$$u_{ihmt} = \alpha_i Ad_{hmt} + \beta_i Dist_{ih} + \gamma_1 Dist_{ih}^2 + \gamma_2 Dist_{ih} \cdot Ad_{hmt} + \mathbf{\Gamma}_h + \varepsilon_{ihmt} \tag{1}$$

where $Dist_{ih}$ is the distance from patient i to hospital h, Ad_{hmt} is the advertising stock (discussed below), $\mathbf{\Gamma}_h$ is the hospital-department fixed effects, and ε_{ihmt} is an idiosyncratic error term. $\alpha_i, \beta_i, \gamma_1, \gamma_2$ represent the parameters.

We include the distance squared term, $Dist^2$, to capture the change in marginal utility of traveling farther. The distance-advertising interaction measures the effect of distance on advertising. For example, an advertising effect of a hospital that is located 5 miles from the patient would differ from that of a hospital that is 10 miles away. Lastly, the fixed-effects, $\mathbf{\Gamma}_h$, capture the time-invariant components for each hospital-department combination.

We allow the patients' preferences to differ by demographics. Note the subscript i on α_i and β_i in Equation 1. We define these parameters as

$$\alpha_i = \bar{\alpha} + \boldsymbol{X}_i \tilde{\alpha},$$

$$\beta_i = \bar{\beta} + \boldsymbol{X}_i \tilde{\beta}$$

where $(\bar{\alpha}, \bar{\beta})$ capture the 'mean-valuations' and the $(\tilde{\alpha}, \tilde{\beta})$ capture the individual heterogeneity in preferences. Intuitively, we interact the patient characteristics, $\boldsymbol{X}_i$, with both advertising stock and travel distance.

The patient characteristics include the following: female, income, age, comorbidity index; and dummies for race, insurance and the department the patient visited. For the variables income, age, and comorbidity index, we redefine them as dummy variables to equal one if it exceeds the median and zero otherwise. This approach aids the interpretation of the results and estimation and thus has been the standard practice in health care literature (e.g., Tay (2003); Gaynor et al. (2015); Kim and KC (2020b)). The comorbidity index denotes the presence of certain health conditions in a patient, where a higher comorbidity index denotes worse patient outcomes. In detail, we use the Elixhauser comorbidity index (Elixhauser et al. 1998), which tracks the presence of 31 diagnoses (e.g., cardiac arrhythmias, hypertension, diabetes, metastatic cancer, obesity) in patients.

There are three categorical variables: department, race, and insurance. The department category (the department of the hospital the patient received care from) consists of brain, cardiac, digestive, pulmonary, and renal. As this variable is not directly observed, we use the patients' primary diagnosis codes to classify them into the corresponding department. For example, "acute myocardial infarction" is classified into "cardiac" department and "intracranial injury" is classified into "brain" department[9]. Regarding races, we use four classifications: white, black, Hispanic and others; where others denote the remaining races. Similarly, we have four insurance types: Medicare, Medicaid, private and others.

The hospital h's advertising stock in a given HSA m and quarter t is defined as [10]

$$Ad_{hmt} = \sum_{\tau=0}^{T} \rho^{\tau} log(1 + ad_{hm,t-\tau})$$

where ρ parameter represents the carry-over of advertising effect[11] and ad_{hmt} is the advertising expenditure ($) per 100 capita. The log specification is used to portray the decreasing marginal effect. The T (in the summation) represents the number of lags, which we set to

[9] see Appendix 12 for more detail.

[10] We use a similar specification to that in Dube et al. (2005); Tuchman (2019); Shapiro (2020).

[11] There has been a long literature on the dynamic effects of advertising. Sethuraman et al. (2011) provide a meta-analyses of 56 papers discussing the short- and long-term advertising elasticities.

one meaning that our specification observes the effect of advertising over two quarters (six months).

Lastly, we set our market definition as a Hospital Service Area (HSA), which is a collection of zip codes whose residents receive most of their hospitalizations from the hospitals in that area. That is, HSA represents a local health care market for hospital care.[12]

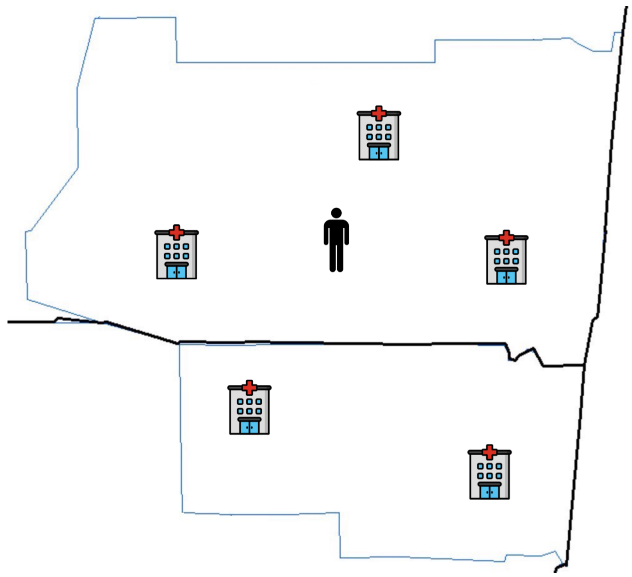
This setting is congruent for our study as it allows us to localize the patients' choices of hospitals. First, hospitals, unlike cereals or detergents, are not ubiquitous. That is, the identical hospital cannot be found in every city or county. Therefore, including every hospital in Florida in a given patient's choice set is implausible. Second, emergency patients are generally sensitive to travel distance. For example, an emergency patient living in Miami (Southeast Florida) will generally not visit a hospital in Jacksonville (Northeast Florida). As emergency patients tend and need to visit the closest hospitals, defining markets as HSAs limits the patient's choice set to the surrounding hospitals of the patient's residence. In our data sample, the median number of hospitals in a choice set is five[13] and the median distance traveled is around 8.5 miles (Table 1).

4.1 Identification

We explain our identification strategy in this section. To identify the effect of hospital advertising, we would need to cross-connect the variation in hospital advertising with the variation in patients' choice of hospitals, while fixing other characteristics.

[12]See https://www.dartmouthatlas.org/faq/ for further details on HSAs.
[13] mean 5.4, standard deviation 1.3, min 2, and max 11

Figure 1: Identification



Our identification strategy (i) rests on the assumption that patients' DMA residence are exogenous; and (ii) uses HSAs (our market definition) that are adjacent to DMA borders. For ease of understanding, we use Figure 1 to help illustrate our identification strategy. This figure shows two HSAs that are in two different DMAs. Patients in each HSA can visit hospitals in both HSAs, however, they can receive advertisements from those hospitals only within the same DMA. This is because hospitals have limited marketing budget thus tend to advertise only inside their own DMA. [14]Therefore, after we control for the observable characteristics and the distance to the hospitals, the only remaining (observable) variation (for the patient) would be the advertising exposure between the various hospitals. We use this exogenous variation in patients' residence and hence the advertising exposure to identify the advertising effect.

A potential concern is that the endogeneity of advertising decisions may bias our advertising effects on patient demand. For example, market structure and the competition between hospitals may influence the hospitals' advertising decisions. A hospital that loses patients may advertise (more) to gain patients, whereas a dominant hospital may also advertise to

[14]Our data shows that all the hospitals except for one advertise inside their DMA only.

maintain the status-quo. Furthermore, a patient may happen to be more exposed to a certain hospital's advertising, increasing the unobserved likelihood of choosing that hospital. These factors in tandem can lead our advertising variables to be correlated with the unobservables.

To address the endogeneity in hospital advertising, we adopt the control function approach. We assume that ε_{ihmt} in Equation 1 can be decomposed into endogenous and exogenous components, $\varepsilon_{ihmt} = f(\nu_{ihmt}) + \eta_{ihmt}$, where ν, η are the endogenous and exogenous components of the error term, respectively.

We recover ν by running the OLS regression as follows

$$Ad_{ihmt} = Z_{ihmt}\gamma + \nu_{ihmt}$$

where Z_{ihmt} is the instrument, an indicator function for whether the patient resides in the same DMA as the hospital. Once we obtain the estimated $\hat{\nu}_{ihmt}$, we simply add them as regressors into Equation 1, leaving η_{ihmt} as the remaining idiosyncratic error term. Therefore, we assume $E\big[\varepsilon|Z,\nu\big] = \delta\nu$, where δ is the additional parameter to be estimated. [15]

We now discuss the validity of our instruments. Similar to Kim and KC (2020b), we use as an instrument an indicator function for whether the patient resides in the same DMA as the hospital. It is easy to see that hospital advertising exposure is correlated with whether the patient resides in the same DMA as the hospital. Hospitals have a limited marketing budget, and therefore, hospitals generally tend to advertise in their own DMAs. We confirm this in our sample—all the hospitals except for one advertised in their own DMAs. Therefore, after controlling for observable and market factors, patients are more likely to receive television advertisements from a hospital if they reside in the hospital's DMA.

However, we believe that the exogenous error term (η) is not correlated with our instrument, a patient-hospital being in the same DMA. Since DMA borders were defined by A.

[15] For detailed discussion on control functions, see Wooldridge (2010) and Petrin and Train (2010).

C. Nielsen in 1995 for general television advertisement, and that most hospitals were built many decades ago, it would be rational to believe that patients do not form preferences based on the DMA delineation (after controlling for distance, hospital, and market factors), particularly because patients are not usually even aware of DMA designations.

4.2 Estimation

We estimate our model using maximum likelihood estimation (MLE). Recall our utility function in Equation 1,

$$u_{ihmt} = \alpha_i Ad_{hmt} + \beta_i Dist_{ih} + \gamma_1 Dist_{ih}^2 + \gamma_2 Dist_{ih} Ad_{hmt} + \Gamma_h + \varepsilon_{ihmt}.$$

Note that we use a control function approach to address the endogeneity in advertising (Section 4.1), letting $\varepsilon_{ihmt} = \delta\hat{\nu}_{ihmt} + \eta_{ihmt}$ (control function residuals). We simplify the utility equation[16] as

$$u_{ihmt} = \tilde{X}_{ihmt}\theta + \eta_{ihmt},$$

where $\tilde{X}_{ihmt}\theta = \alpha_i Ad_{hmt} + \beta_i Dist_{ih} + \gamma_1 Dist_{ih}^2 + \gamma_2 Dist_{ih} Ad_{hmt} + \mathbf{\Gamma}_h + \delta\hat{\nu}_{ihmt}$ and $\theta = (\alpha_i, \beta_i, \gamma_1, \gamma_2, \delta, \rho)$ denotes the parameters. Now, assuming that η_{ihmt} is i.i.d. standard Type-I Extreme Value, we derive the probability of a patient i choosing a hospital h in market m and time t as

$$Pr_{ihmt}(\theta|\tilde{X}) = \frac{exp(\tilde{X}_{ihmt}\theta)}{1 + \sum_{k\in H_m} exp(\tilde{X}_{ikmt}\theta)}.$$

Consequently, we estimate θ through MLE by maximizing the log-likelihood

$$LL(\theta|\tilde{X}) = \sum_i^I \sum_h^H \sum_m^M \sum_t^T y_{ihmt} log\big(Pr_{ihmt}(\theta|\tilde{X})\big),$$

[16]With some abuse of notation.

where $y_{ihmt} = 1$ if patient i chose the hospital h, and zero otherwise.

5 Reduced Form Evidence

In this section, we use ordinary least squares to gain a brief understanding of the advertising effectiveness. Specifically, we regress advertising on three dependent variables: distance (from patient) to hospital, indicator for patient's death, and demand for hospitals.[17] We first transform the advertising into log specification, ($log(1 + ad)$), to portay the concavity and to match our logit specification. To aid the interpretation of the results, we further transform distance and demand variables such that the models are in a log-log form. As the distance and death indicators are patient-level measures, we further control for patient characteristics. Table 3 summarizes the results.

Column (1) presents the results regarding distance. We find that advertising has a positive and statistically significant impact on patient's distance traveled. Our log-log form shows that, on average, a 1% increase in advertising expenditure increases the patient's distance by approximately 1.36%. Elder and female patients were less likely to travel farther, whereas the wealther patients were more likely to travel. We do not find evidence that comorbidity levels affect the travel distance, that is, whether the patient is relatively more severe or not did not have an influence on their travel distance. We also find that advertising is positively associated with patient's mortality, as seen in column (2). As expected, the older the patient, the higher the mortality. Female patients had a relatively lower mortality rate, and the same for wealtheir patients. Lastly, column (3) presents the advertising effectiveness on patient demand.[18] This result shows that advertising and demand for hospitals are postively correlated, providing some evidence that advertising can be an effective tool for hospitals in gaining market share. In summary, our reduced-form results suggests that advertising can (i) harm patients by increasing their travel distance and mortality rates; but

[17] total emergency patient volume in a given quarter.

[18] As the hospital demand is not recorded on a patient-level, we do not control for patient characteristics in Model (3).

(ii) benefit hospitals by gaining greater patient demand.

Table 3: Reduced Form Results (OLS)

	Dependent variable		
	(1) $log(Dist_{ph})$	(2) $Died_p$	(3) $log(Demand_{hmt})$
$log(1 + ad_t)$	1.3555***	0.6754***	0.3572**
	(0.3475)	(0.0859)	(0.1590)
Age	-0.0023***	0.0011***	—
	(0.0002)	0.0004	
Female	-0.0174***	-0.0064***	—
	(0.0034)	(0.0010)	
log(Income)	0.4959***	-0.0062**	—
	(0.0984)	(0.0027)	
Comorbidity	0.0016	-0.0124***	—
	(0.0010)	(0.0007)	
FE	Yes	Yes	Yes
N	302,135	302,135	1,566

Note: Models (1) and (2) contain hospital-department, county, and time fixed effects. Model (3) contains hospital, market, and time fixed effects. Standard errors are clustered at hospital level. Significance: **p <0.05; ***p <0.01.

6 Results

This section presents the results from the hospital choice model. Due to the number of variables, we partition the results into two. Table 4 shows the results regarding the advertising variables and Table 6 shows the results regarding distance variables.

6.1 Hospital Choice Model

6.1.1 Effect of Advertising

We first discuss the effect of advertising on patient choices in Table 4. We find that advertising positively affects patients' choices, and this result is highly statistically significant. Another unique finding is that the advertising effect decreases as the hospital is further away from the patient. A hospital that is located 20 miles from a patient would have approximately 8% less advertising effect than a hospital that is 10 miles from a patient[19], holding all other variables fixed. Regarding demographics, female and higher income patients are relatively less sensitive to advertising, whereas the elder, and patients with higher comorbidity levels are more sensitive to advertising. The female coefficient, however, is not statistically significant, which could mean that gender does not play a significant role in selecting hospitals for emergency patients.

We discover that the department interaction estimates are generally the greatest in magnitude with respect to advertising, suggesting that the patient's medical conditions were the greatest contributing factor to hospital choice. The cardiac patients were the least sensitive to advertising, although the difference with the brain patients is not found to be statistically significant. For the remaining two categories, race and insurance, there is no strong evidence of a difference in the advertising effect within the two categories.

[19] $-0.0306/(4.0744 - 10 \times 0.0306) = 0.0812$

Table 4: Demand Results – Advertising

	Estimate	Significance
Advertisement	3.4336	***
Interactions		
Distance	-0.0227	***
Female	-0.0024	
Higher Income	-0.2319	***
Older	0.0788	**
Comorbidity	0.1277	***
Department		
Brain	0.0687	
Pulmonary	0.2312	***
Digestive	0.2542	***
Renal	0.1377	**
Race		
Hispanic	-0.0641	*
Black	0.0366	
Other	-0.0190	
Insurance		
Medicaid	-0.0659	
Private	-0.0263	
Other	0.0151	

Notes: The references [department, race, insurance] are [cardiac, white, Medicare]. Regression also includes hospital-dept. fixed-effects. Standard errors are corrected for the two-step estimation. Significance: *p <0.1; **p <0.05; ***p <0.01.

Lastly, Table 5 provides results on the control function residuals and the advertising carryover. The statistically significant coefficients on the residuals provide evidence that there is endogeneity in advertising. If this endogeneity had not been addressed, the advertising estimate in Table 4 would have been biased downwards. The 0.5568 carryover means that 55.68% of the advertising effect still persists in the next quarter. In other words, the effect of advertising now would decrease by approximately 90% after a year, ceteris paribus[20].

[20] $1 - 0.5568^4 = 0.9039$

Table 5: Demand Results – Other

	Estimate	Significance
Control Function Residual	-3.2033	***
Advertising Carryover (ρ)	0.5568	***

Note: Standard errors are corrected for the two-step estimation. Significance: **p <0.05; ***p <0.01.

6.1.2 Role of Distance

We will now discuss the role of distance in Table 6. The results provide evidence that the patients do not like to travel and the patients' disutility for traveling farther decreases.[21] Furthermore, patients that are either female, higher income, and older have a greater dislike for traveling. On the other hand, patients with higher comorbidity levels (a proxy for a patient's health condition) are more sensitive to distance. This may be due to the fact that patients with more severe conditions are relatively more sensitive to the quality of care and also need immediate care; thus, distance matters more than for patients with less severe conditions.

Regarding the categorical variables, the reference variables for department, race, and insurance are cardiac, white, and Medicare, respectively. For the department interactions, we find that the estimates are all highly statistically significant. The results show that the patients with cardiac-related (reference) diagnoses have the greatest dislike for traveling. Patients with other diagnoses seem to have similar sensitivity to distance, as seen from the comparable magnitude of coefficients. A possible explanation could be that cardiac disorders are one of the diagnoses with the highest mortality rate. Therefore, these patients could care more about the "quality" of the hospital rather than the distance to hospitals per se. Similar to the results on advertising, the magnitude of the coefficients of department interactions is

[21] The root of $0.0019x^2 - 0.2355x = 0$ is approximately 124 (and 0). Every patient in our analysis traveled less than 124 miles and henceforth dislikes traveling.

greater than that of other interactions, which further confirms that the medical conditions were the most important in patients' choices for hospitals.

For the race category, we find that white patients were the most sensitive to distance traveled and that black patients dislike traveling compared to white patients. Regarding insurance, private insurers are most willing to travel. This may be be due to the fact that private insurers have a larger network than Medicare insurance networks.

Table 6: Demand Results – Distance

	Estimate	Significance
Distance^2	0.0017	***
Distance	-0.2313	***
Interactions		
Female	-0.0023	**
Higher Income	-0.0115	***
Older	-0.0026	*
Comorbidity	0.0040	***
Department		
Brain	0.0245	***
Pulmonary	0.0218	***
Digestive	0.0192	***
Renal	0.0236	***
Race		
Hispanic	-0.0023	
Black	-0.0051	***
Other	-0.0040	
Insurance		
Medicaid	0.0086	***
Private	0.0114	***
Other	0.0028	

Notes: The references [department, race, insurance] are [cardiac, white, Medicare]. Regression also includes hospital-dept. fixed-effects. Standard errors are corrected for the two-step estimation. Significance: *p <0.1; **p <0.05; ***p <0.01.

7 Counterfactual Simulation: Advertisement Ban

This section presents our counterfactual analysis—what would have happened in a world without hospital TV advertisements. We proceed with background information on hospital advertising policy followed by the results.

The U.S. and New Zealand are the only countries in the world that fully allow hospital DTCA. Even in U.S., the American Medical Association (AMA), viewing hospital advertising as "derogatory to the dignity of the profession" had banned hospital advertising until 1980. Although the ban was overruled by a circuit appellate court in 1980, there are ongoing debates on the adequacy of hospital advertisements. For example, Schenker et al. (2014) argue that hospital DTCA can misinform potential patients and should be regulated similar to prescription drug advertising. The Food and Drug Administration regulates pharmaceutical advertisements, whereas the Federal Trade Commission oversees hospital advertisements. This could mean that hospital advertisements could be handled by the federal government in a manner similar to that for consumption goods such as detergents and clothes, although health care decisions are far more difficult to make. When it comes to selecting health care services, it is difficult to determine whether patients have made the right decision. Furthermore, in 2011, the Vermont state representative Maier introduced an act to ban hospital advertising, questioning the necessity of hospital advertising – "it's not producing health care."

Nonetheless, our focus is not to take sides on the debate, but rather to quantify and examine the potential impacts of hospital advertising on the emergency patients. In further detail, we analyze how a ban on hospital advertising would affect the patient's distance traveled and their mortality rates. Recall our earlier results that advertising influences emergency patient choices of hospitals. If patients switch hospitals due to advertising, they will encounter a change in their (i) travel distance and (ii) quality of care received. Using the patient choice model, we calculate each patient's choice probabilities of hospitals under the counterfactual scenario and use these to analyze the changes in patient's distance traveled and mortality outcomes. Results are discussed in the the following sections.

7.1 Change in Patient Distance

Table 7 provides the results comparing the travel distances with and without advertisements. Our findings suggest that patients travel approximately 1.2 miles (13.5%) farther due to ads; in other words, patients would choose closer hospitals in a world without hospital advertisements. Furthermore, the variance of the travel distance also increases. A possible explanation might be that advertising attracts patients from a further distance and also extends the choice set of a patient, leading to an increase in variance. These findings demonstrate that advertising is beneficial for hospitals, i.e., hospitals can effectively widen their patient base and draw in patients from a farther distance by using television advertising. For the emergency patient, traveling further may risk one to exceed the 'golden-hour'. We discuss the impact of distance on mortality in the next section.

Table 7: Change in Patient Travel Distances

	Mean		Variance	
	Ads Ban (CF)	With Ads (Data)	Ads Ban (CF)	With Ads (Data)
Travel Distance	8.83	10.03	4.40	7.63
Difference (Data - CF)	1.20		3.23	
95% confidence interval	(1.13, 1.27)		—	
Overall change due to ads	Increase		Increase	

Note: The null hypothesis is that travel distance and the counterfactual travel distance come from the same normal distributions with equal means and equal variances. The confidence intervals are around the difference of the population means.

7.2 Change in Patient Mortality

In this section, we first describe the procedure of our mortality analysis. Then, we discuss the results and conclude by highlighting the importance of travel distance on emergency patients. [22]

We construct a linear probability model of patient mortality similar to that in Gowrisankaran and Town (1999); Geweke et al. (2003). In our model, we regress an indicator for whether the patient p who was treated at hospital h has deceased ($Died_{ph}$) on (i) travel distance of patients ($Travel_{ph}$) and its squared ($Travel_{ph}$); (ii) a set of patient demographics and variables (X_p); (iii) hospital dummies (H_h), which denotes the hospital choice of the patient p; (iv) a dummy for whether the patient visited during the weekend ($Weekend_p$); and (v) fixed effects (FE) for patients' admission hour and urban-rural classifications.

The model is as follows:

$$Died_{ph} = \alpha_1 Travel_{ph} + \alpha_2 Travel_{ph}^2 + \beta X_p + \gamma H_h + \delta Weekend_p + FE + \varepsilon_{ph}, \tag{2}$$

and in this framework,γ is interpreted as the risk-adjusted mortality rate for each hospital.

As Gowrisankaran and Town (1999) mention, the problem of selection bias arises in hospital choice. Sicker patients may visit a higher quality hospital, creating a correlation between the unobserved residual (ε_{ph}) and hospital fixed-effects (H_h). Furthermore, as we include travel distance ($Travel_{ph}$) as a regressor, $Travel_{ph}$ is also endogenous, as patients may travel more or less depending on their medical conditions.

We instrument *travel* distances ($Travel_{ph}, Travel_{ph}^2$) with advertising volume within patient's HSA relative to that of DMA (AV_p, AV_p^2), and hospital dummies with distance to *all* hospitals ($Dist_{ph}, Dist_{ph}^2$), following the standard procedure (Gowrisankaran and Town 1999; Geweke et al. 2003; Kim and KC 2020b). It may seem puzzling due to the presence

[22] We compare the results from our model and that from Gowrisankaran and Town (1999) in Section 7.2.1.

of two distance variables, however, there are no correlations between the two. If a patient's observed travel distance is relatively short, this does not imply that all the hospitals were of close range. Even if we take it to the extreme and posit that every emergency patient chose the closest hospital, there still would not be no trends between the two distance variables because the distance to hospitals vastly differ both inter- and intra-markets. Therefore, the former, $Dist_{ph}$, captures the notion of the intrinsic distance between the patient and the various hospitals within a given choice set (*state* variable), whereas the latter, $Travel_{ph}$, captures the distance *traveled* by the patient (*action* variable).

The validty of the instruments are as follows. First, if there is more advertising in a given HSA relative to its DMA, it would mean that the patient residing in that HSA is more likely to visit closer hospitals. Therefore, this measure would be negatively correlated with patient's travel distance to hospitals. Our exclusion-restriction is satisfied as we believe that hospitals' advertising decisions do not depend on one's *unobserved* illness, and morevoer, hospitals are not able to target advertising at the individual level. Second, distance to hospital ($Dist_{ph}$) is negatively correlated with the choice of the hospital as patients do not like to travel. 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.[23] The first stage F-statistics for all the instrumental variable regressions are high[24], which validates the power of our IVs.

The results of mortality LPM are discussed next. Looking at Table 8, the distance coefficient is positive as we expected. Distance squared coefficient is negative, meaning that the effect of distance on patient's mortality rate decreases as patients travel further. We find that, on average, traveling an initial 10 miles can increase one's mortality rate by 1.34 percentage points, holding other factors constant. The 1.34 percentage point may not seem like much *per se*, but this corresponds to a 27% increase for a patient with a mortality rate

[23]see Gowrisankaran and Town (1999) for detailed discussion.

[24]F-statistics for (i) hospital FE, H_h: (mean, 25%, 75%) = (235.8, 22.1, 282.5); and (ii) travel distance, $Travel_{ph}$: 355.7

of 5%. Patients that are admitted during the weekend have a slightly higher mortality rate, and female patients have a slightly lower mortality rate. As one would expect, older patients have, on average, a higher mortality rate.

Cardiac-related diagnoses have the highest mortality rate, though the difference between the pulmonary-related diagnoses was not found to be significant. Compared to the white race, hispanic patients have a lower mortality rate, and the difference is highly statistically significant. Regarding insurance, patients with private insurance plans tend to have the lowest mortality rate.

Table 8: Patient Mortality Model

	Estimate	Significance
Distance	0.0020	**
Distance Squared	-0.0001	*
Patient Characteristics		
Weekend	0.0060	***
Female	-0.0078	***
Log Income	-0.0039	
Age	0.0010	***
Comorbidity	-0.0137	***
Department		
Brain	-0.0820	***
Pulmonary	-0.0011	
Digestive	-0.1006	***
Renal	-0.0726	***
Race		
Hispanic	-0.0141	***
Black	-0.0003	
Other	0.0110	**
Insurance		
Medicaid	0.0034	
Private	-0.0202	***
Other	0.0008	

Notes: The references [department, race, insurance] are [cardiac, white, Medicare]. Regression also includes hospital fixed-effects. Standard errors are clustered at hospital level. Significance: *p <0.1; **p <0.05; ***p <0.01.

To examine the change in mortality rates under the counterfactual scenario, we combine the results of our LPM with the hospital choice model. We associate the counterfactual choice probabilities and the following counterfactual distance (under the advertising ban) with the LPM parameters in Table 9. Following Gaynor et al. (2016), we compare the expected mortality rates[25] to determine how the advertising ban affects the population-level patient mortality.

Results are summarized in Table 9. Our findings show that advertising could increase patient mortality rates overall. Patients travel farther, but what is more surprising is that patients switch to lower-quality hospitals, although their ex-ante rationale for switching hospitals would have been to receive a higher quality of care. Under an advertising ban, the expected mortality rate is 6%, which is lower than the base mortality rate (6.09%). A simple calculation shows that for every 1 million ED patients, 809 more lives would be saved. Our findings are consistent with Kim and KC (2020b) in terms of direction, although our results statistically significant. The discrepancy between the two studies might be due to the sample selection, as Kim and KC (2020b) analyzes the effect on general inpatients, whereas our focus in on emergency patients.

Table 9: Change in Patient Mortality Rate

	Ads Ban (CF)	With Ads
Mean Mortality Rate	0.06005	0.06086
Difference (Data - CF)	0.00081	
95% confidence interval	(0.00016 0.00146)	
Overall change due to ads	Increase	

Note: The null hypothesis is that patient's mortality rate and the counterfactual mortality rate come from the same normal distributions with equal means and equal variances. The confidence intervals are around the difference of the population means.

[25] Expected mortality rates with and without ad. $\mathbb{E}[\Delta Mort] \equiv \mathbb{E}[Mort^{Ad}] - \mathbb{E}[Mort^{NoAd}]$

We further analyze the the factors of the mortality changes, by decomposing the increase in mortality into two factors: distance and treatment quality. We compute our findings by substituting each of the factor in Equation 2 with that of the counterfactual and then calculating the proportion of each factor. Table 10 summarizes the findings. We find that quality of care accounts for approximately three quarters of the change in mortality rates. Our results show that 76.1% of the increase in mortality is due to change in quality of treatment, and the remaining 23.9% is due to change in distance.

Table 10: Mortality Rate Decomposition

	Difference	Proportion
Overall difference in mortality rate	0.00081	—
Change due to quality of care	0.00062	76.11%
Change due to travel distance	0.00019	23.90%

Note: Difference is rounded to five decimal points. Proportion calculated before rounding hence the value mismatch.

7.2.1 Comparison

In this section, we show the importance of controlling for travel distance for emergency patients. Emergency patients had not been the core focus of researchers, as the preceding literature mainly examined the outcomes of general patients. General patients have sufficient time to consider hospitals and usually book appointments ahead of time. Therefore, it seems plausible not to consider the travel distance as one of the factors underlying mortality. However, our results show that traveling an initial 10 miles can increase an emergency patient's mortality risk by 1.3 percentage points. (Table 8). For a patient with a mortality rate of 5%, this is equivalent to a 27% increase.

In Table 11, we compare the results with and without controlling for distance. Column (1) presents the results from our model (i.e., the results in Table 9) and column (2) presents the results derived from the model without controlling for distance (i.e., the preceding model).

Both models show that hospital advertising increases mortality rates, however, the difference in mortality rate is greatly overestimated when one does not control for distance. Our findings indicate that when one studies the mortality outcomes of emergency patients, one should take into account the significance of travel distance.

Table 11: Mortality Rate Comparison

	(1) Our Model	(2) Preceding Model
Overall difference in mortality rate (%)	0.00081	0.00142
95% confidence interval	(0.00016 0.00146)	(0.00077, 0.00207)
Distance controlled	Yes	No
Overall change due to ads	Increase	Increase

Note: The null hypothesis is that patient's mortality rate and the counterfactual mortality rate come from the same normal distributions with equal means and equal variances. The confidence intervals are around the difference of the population means. Values are rounded to five decimal points.

8 Conclusion

Our analysis provides evidence that advertising affects not only general patients but also emergency patients. We further show that the advertising effect declines as the hospital is further away from the patient. The choice model results show that out of the patient characteristics, a patient's medical condition was the most important factor in choosing hospitals.

Our empirical setup allows us to examine a policy simulation, an advertising ban. Comparing our results to the counterfactual scenario, we find that prohibiting hospital advertising could decrease both patient's distance traveled and mortality rates overall. Using an instrumental variable (IV) setting, we model patients' mortality rates on various variables and find that traveling an additional 10 miles can increase one's mortality rate by 1.3 percentage points, holding all other variables constant. The results indicate that under an advertising ban, the expected mortality rate decreases. We further decompose this change in mortality into two factors: distance and quality of care. We find that 76% of the change in mortality is due to change in treatment quality, and the remaining 24% is due to change in distance.

Our findings that hospital advertising influences emergency patients and their health outcomes may inform policymakers about hospital advertising in the current changing healthcare environment. Exploring the impact of advertising on patient choice and outcome is a rich topic for future research with significant managerial and policy implications, especially given the growing importance of consumer-driven healthcare in the U.S. economy.

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Appendix

A Data Cleaning Process

Table 12: Diagnosis Codes and Department

Code	Diagnosis	Department
85	Coma; stupor; and brain damage	1
100	Acute myocardial infarction	3
103	Pulmonary heart disease	2
107	Cardiac arrest and ventricular fibrillation	3
108	Congestive heart failure; nonhypertensive	3
109	Acute cerebrovascular disease	1
115	Aortic; peripheral; and visceral artery aneurysms	3
116	Aortic and peripheral arterial embolism or thrombosis	3
131	Respiratory failure; insufficiency; arrest (adult)	2
153	Gastrointestinal hemorrhage	4
157	Acute and unspecified renal failure	5
233	Intracranial injury	1

Note: The code corresponds to Clinical Classifications Software (CCS) for ICD-9-CM. https://www.hcup-us.ahrq.gov/toolssoftware/ccs/AppendixCMultiDX.txt
Department: 1: Brain / 2: Pulmonary / 3: Cardiac / 4: Digestive / 5: Renal