The Impact of Limited Consideration on Market Outcomes in the Hospital Industry

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Abstract

This paper introduces a random consideration sets model of hospital demand to analyze market interactions while relaxing the assumption that patients necessarily consider all options available from within their contracted networks of providers. A key contribution of the model is its ability to quantify the impact of bounded rationality on equilibrium market outcomes when firms compete for attention. The demand model identifies and estimates the probability that each patient considers and chooses each in-network hospital within a geographic radius of their home. On the supply side, hospitals compete in a two-stage game: (i) with each other for patients' attention through advertising expenditure, and (ii) with insurers through Nash-in-Nash bargaining over prices. Assuming full consideration in hospital demand biases distance elasticities downward in magnitude, as it fails to account for attention decreasing with distance. Counterfactual simulations show that limited consideration decreases hospital accessibility and acts as an artificial form of product differentiation. Calibrated to the national level, baseline results imply that annual US hospital expenditure could be reduced by approximately $36 billion if privately insured patients had full consideration. A retrospective merger is used as a natural experiment, providing evidence that

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accounting for bounded rationality in models of imperfect competition can improve the accuracy of counterfactual predictions.

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1 Introduction

Traditional discrete choice demand models assume that consumers are fully attentive to all available options. In markets for informationally-intensive products, such as hospital care, this assumption may contrast with how real-life decisions are made. Survey evidence suggests that 88% of US adults have "less than proficient" health literacy (Kutner et al., 2006).[1] In the presence of these informational constraints, hospital patients[2] are unlikely to consider all options covered by their insurer upon having a health shock requiring inpatient hospital care. Erroneously assuming choices from a perfectly perceived set of contracted hospitals reveal preferences when real-life patients are inattentive may lead to flawed policy recommendations as a result of biased estimates of preferences and substitution patterns.

This paper introduces a random consideration sets[3] model of hospital demand to analyze market interactions while relaxing the assumption that patients necessarily consider all options offered by their contracted insurer. A foundational contribution of the model lies in measuring the effects of bounded rationality on equilibrium market outcomes when firms compete for attention. The model is applied to ask two central questions. First, how does limited consideration affect market outcomes, particularly in terms of pricing and access to hospitals? Second, how does accounting for limited consideration improve the accuracy of predictions about mergers, and what underlying mechanisms explain these changes?

The 2023 US DOJ/FTC Merger Guidelines broaden the scope of antitrust analysis by offering a more comprehensive assessment of non-price competition, which has become increasingly important in modern markets (Athey and Nevo, 2023; U.S. DOJ and FTC, 2023).[4] Evidence suggests that the average American adult spends approximately 5.6

[1]The Centers for Disease Control and Prevention (CDC) define personal health literacy as "the degree to which individuals have the ability to find, understand, and use information and services to inform health-related decisions and actions" (Santana et al., 2021).

[2]Note that "patients" and "consumers" may be used interchangeability throughout, with the exact terminology used depending on context.

[3]A "consideration set" refers to the unobserved set of hospitals that a patient chooses from.

[4]"Competition often involves firms trying to win business by offering lower prices, new or better products and services, more attractive features, higher wages, improved benefits, or better terms relating to various

hours per day consuming ad-supported content (Evans, 2020), but economists do not have tools to measure how the subsequent competition for attention affects market outcomes. Understanding the causes and consequences of the rise in market power—the decades-long trend towards an increasing ability of firms to unilaterally raise prices—has sparked significant research interest (e.g., Berry et al., 2019; De Loecker et al., 2020; Döpper et al., 2024). This paper highlights bounded rationality as a critical yet seemingly overlooked source of market power in the hospital industry, where prices have grown more than any other sector of the US economy over the past two decades (Brot-Goldberg et al., 2024).

In addition to price effects, the market segmentation brought about by limited consideration also restricts health care access, defined as the "degree of fit" between the patient and medical service (Penchansky and Thomas, 1981). It has been previously recognized that patients' inattention should be integrated into conventional frameworks for understanding health care access (Saurman, 2016).[5] This paper provides the first empirical evidence that in addition to barriers such as distance to care and a lack of insurance coverage, patients' inattention to all contracted options is an economically significant obstruction to hospital access.

Random consideration sets models, as initially proposed by Manski, 1977, estimate choice probabilities by integrating over unobserved heterogeneity in consideration sets. Patients are modeled as choosing from a finite mixture of consideration sets, weighted by the probability of each set being realized, and preferences are estimated conditional upon unobserved consideration set realization. This paper's random consideration sets model is embedded in an option-demand market (Capps et al., 2003) where insurance intermediaries assemble networks of hospitals to sell to consumers who are uncertain about the circumstances under which they will require care.

Existing models of hospital-insurer bargaining allow for consumers to face uncertainty over the exact circumstances they will require medical services throughout the contract, but assume that choice sets conditional upon a health shock are known with certainty.

additional dimensions of competition."(U.S. DOJ and FTC, 2023)

[5] "It seems that awareness has become an assumed dimension of health care access. No health care service can be effective if it does not respond to context or if the intended population does not know it exists. Like other dimensions of access, awareness facilitates the fit between patient and the service" (Saurman, 2016).

This paper relaxes this assumption, allowing for more general forms of unobserved heterogeneity that permit more flexible substitution patterns.[6] By assimilating the random consideration and option-demand frameworks, this paper offers a novel approach that not only addresses previously unanswerable policy-relevant questions but also readily extends to a wide range of applications in other two-sided markets beyond the current context (i.e., digital platforms).

Hospitals and insurers compete in a two-stage game of advertising and bargaining to determine equilibrium prices and insurance networks. The price any hospital is able to negotiate with an insurer is a function of the value it brings to the insurer's network. This value is defined as patients' willingness-to-pay (WTP) to have a hospital included in their network. When choosing a hospital, patients derive no value from options not being considered. Thus, limited consideration induces hospitals to engage in competitive advertising to become more salient, shaping patients' perceptions of the feasible set of alternatives.

From 2008 to 2016, nearly half of U.S. acute care hospitals invested in advertising, collectively spending \$3.39 billion (Ndumele et al., 2021). Anecdotal evidence suggests that hospital systems use advertising to compete for patients' attention. In response to a dominant Massachusetts hospital system significantly increasing its advertising budget, the president of a healthcare marketing firm remarked, "they want to expand their brand awareness, reach more patients, and grow their patient base. I understand why other hospitals in the area are concerned. They should be" (Bartlett, 2022).

After measuring how hospitals with higher WTP can negotiate higher prices, this relationship can be used to predict how prices will likely change if two hospitals merge. This involves assessing how substitutable the merging hospitals' services are.[7] For example, if hospitals A and B are near perfect substitutes and propose to merge, the insurer's ability to negotiate with A is weakened, as B is no longer an outside option. Post-merger, A and B negotiate jointly, forcing the insurer to include both or neither, which lowers the insurer's bargaining position and raises prices. Additionally, my model allows for the level of substitutability to endogenously change post-merger through advertising competition.

[6] See Appendix D for a detailed discussion of this point.

[7] Proposition 1 in Appendix A formalizes this point.

Existing merger screening methods first define a set of substitute products for each consumer before estimating demand functions to predict price changes (Whinston, 2008). However, these methods assume some degree of substitutability before measuring it (Kaplow, 2010). My model adopts a more flexible approach: the econometrician first defines all *potential* substitutes before jointly estimating both the probability of each subset being realized and the corresponding demand functions.

Estimation results indicate that travel distance reduces both utility and attention, while advertising has a positive effect on attention.[8] The median patient-hospital pair has a choice elasticity with respect to travel distance that is nearly twice the magnitude of what a full consideration model predicts. In a full consideration model, patients' tendencies to choose nearby hospitals is attributed entirely to variation in preferences. In contrast, my model accounts for both (i) travel costs and (ii) reduced attention to distant options. This discrepancy in explaining observed choices directly impacts predicted substitution patterns, which ultimately shape negotiated prices.

Patients' inattention effectively reduces the number of available substitutes. From their perspective, this is functionally similar to a smaller number of hospitals being in the market. While bounded rationality can theoretically act as an artificial form of product differentiation (Grubb, 2015; Spiegler, 2011), measuring its impact on market outcomes from structural demand models has proven difficult due to the endogeneity of firm behavior.[9]

A first counterfactual simulation provides evidence that if patients were fully attentive to all in-network hospitals, the resulting less segmented market would lead to lower average negotiated prices and less dispersed prices across hospitals. The average hospital-plan has a 8.86% ($1,095) lower average price per discharge, with the largest price reductions occurring at hospitals with initially higher prices. A back-of-the-envelope calibration to the national level suggests that annual hospital expenditures paid for by private insurers could be reduced by approximately $36 billion if patients were willing and able to consider all in-network hospitals.[10] Additionally, with prices held constant, aggregate patient

[8] As discussed in Section 6.1, the demand model is identified from advertising being excluded from utility. Reduced-form evidence in support of this assumption is provided in Section 4.

[9] As discussed in Grubb, 2015, a recurring theme in the theoretical literature on behavioral consumers is that firm behavior is endogeneous to consumers' limitations.

[10] In this counterfactual, as throughout the paper, I hold insurance networks fixed.

welfare increases by approximately 59%. The median patient would require an annual compensation of $376 to be as well off as if they were fully attentive.

While hospital prices in the U.S. have increased significantly over the past few decades, these increases have been uneven across competitors. Research has shown that hospital prices vary substantially across hospitals within the same market, even for plausibly undifferentiated services such as lower-limb MRI scans (Cooper et al., 2019).[11] Hospitals that negotiate lower prices than competitors may be at a higher risk of closure.[12] My findings suggest that limited consideration contributes to increased price variation across hospitals. In the counterfactual scenario where patients fully consider all available options, the dispersion of negotiated prices decreases. Interestingly, some hospitals with initially lower prices experience price increases in the less segmented market. Although this paper does not offer a micro-foundation for how consideration sets form, these results align with search-theoretic models (e.g., Burdett and Judd, 1983) which demonstrate that search costs can increase price dispersion.

Recognizing inattention as a driver of market power naturally leads to examining how mergers might exacerbate these effects. To successfully challenge a horizontal merger in the US, the government must show that a "substantial lessening of competition" is "sufficiently probable and imminent" ("Clayton Antitrust Act", 1914). In the 2020 civil district court case *Federal Trade Commission v. Thomas Jefferson University* involving a proposed merger between two Philadelphia-area health systems, a federal judge ruled that competition authorities had failed to meet this burden of proof. However, retrospective analysis indicates that the merger has led to statistically and economically significant price increases relative to a nationwide set of control hospitals.

In a second counterfactual simulation, the assumptions made in this paper's structural model are validated by a natural experiment that utilizes a retrospective contested hospital merger to assess the accuracy of model predictions. Results imply that a standard model would fail to predict the potential for anti-competitive effects. Post-merger shifts in the

[11] Cooper et al., 2019 show that in the Philadelphia region, which is where the data used in this paper comes from, the coefficient of variation across hospital-level prices for lower-limb MRI scans, a plausibly undifferentiated service, is 0.482.

[12] For example, there were 136 rural hospital closures throughout the US between 2010 and 2021 (American Hospital Association, 2022).

distribution of consideration sets play an important role in driving predicted price changes.

The rest of this paper is organized as follows. The next section reviews the literature and provides relevant details about the US hospital industry. Section 3 describes the data. Section 4 presents reduced-form evidence that hospital advertising alters demand, primarily by informing patients rather than shifting utility. Section 5 develops the structural model, followed by Section 6, which details its identification and estimation. Estimation results are presented in Section 7. Section 8 computes a full consideration counterfactual, demonstrating how patients' bounded rationality artificially differentiates hospitals and reduces access to care. Section 9 outlines the method for computing price effects of ownership changes and decomposes the price impact of mergers into three components. A retrospective merger simulation is incorporated to compare the model's performance with existing methods. Section 10 concludes.

2 Literature Review

Industry Background

The U.S. hospital industry plays a pivotal role in the nation's healthcare system, accounting for approximately 6% of GDP. Hospitals provide a wide range of critical services, from emergency care to specialized surgeries, making them central to the delivery of healthcare. Understanding how hospitals interact with both insurers and patients is crucial for analyzing market outcomes.

Option-demand markets are defined as markets where consumers purchase the right, but not the obligation, to consume a product or service at a later time. The classic example is health insurance (Capps et al., 2003), where insurance intermediaries assemble networks of medical care providers (i.e., hospitals) through bilateral bargaining before any health shocks are realized. Conditional upon these negotiations, insurance networks form, insurance plans set prices, and downstream decision makers (either individuals or employers) choose plans.

From 1998 through 2021, there were 1,887 hospital mergers throughout the US (Levins, 2023). Evidence suggests that this consolidation has played a significant role in driving price increases (Cooper et al., 2019; De Loecker and Fleitas, 2021). Multi-hospital systems (MHS) are hospital firms that own multiple locations and jointly negotiate with insurers. MHSs benefit from joint bargaining through the ability to internalize substitution in order to lower insurers' threat points in bilateral negotiations. From 2000-2020, the US hospital bed capacity share of MHSs increased from 58% to 81% (Andreyeva et al., 2022). Within this paper's model, increases in prices are manifested by insurers paying higher costs. In reality, research suggests that insurers pass cost increases approximately one-for-one onto patients through higher health insurance premiums (Brot-Goldberg et al., 2024). From 2007-2017, private health insurance premiums increased by approximately 55% (Cooper et al., 2019).

Traditionally, US merger guidelines have relied heavily on market shares and concentration measures to assess the potential anti-competitive effects of proposed mergers. This permitted the use of ad-hoc methods based on aggregate patient flows in merger screening, rather than methods more consistent with economic theory. Beginning in the 2000s, antitrust enforcement of hospital mergers became stronger than in previous decades due to both the introduction of retrospective studies showing price increases of previously unchallenged mergers and the introduction of structural econometric methods to model price formation in hospital markets.

More flexibility in the methodology used in merger screening is now permitted, and estimates obtained from structural models such as diversion ratios, upward-pricing pressure, and willingness-to-pay have become more regularly used (Farrell et al., 2011). The development of these models has allowed the FTC to challenge proposed hospital mergers more successfully. From 2008-2016, the FTC challenged 16 general acute care hospital mergers and was successful in 12 of them (Brand et al., 2023).

Using a sample of nearly all US hospital mergers from 2007-2011, (Cooper et al., 2019) show that retrospective mergers of hospitals located within 5 miles on average lead to 6% higher prices than control hospitals, with this number staying positive but declining with distance up to 25 miles. In addition to price effects, there is a breadth of evidence that mergers do not lead to quality improvements in terms of patient health outcomes (Dafny et al., 2020; Gaynor et al., 2023; Kessler and McClellan, 2000) or marginal cost savings (Craig et al., 2021). Given the shear size of the sector as well as its connection to labor markets through employer-sponsored insurance, price increases also have consequences that affect broader measures of economic activity in the surrounding area. Brot-Goldberg et al., 2024 show that a merger-induced one percent price increase is associated with an average 0.27% decrease in income per-capita in the counties of the merged hospitals.

Concurrent to increasing concentration has been a trend towards more hospital advertising expenditure. Before 1980, medical advertising was heavily regulated by the American Medical Association's (AMA) Code of Conduct. In the 1982 case *AMA v. FTC*, this was ruled as an anti-competitive practice, stating that "ethical principles of the medical profession have prevented doctors and medical organizations from disseminating information on the prices and services they offer, severely inhibiting competition among health care providers" (AMA v. FTC, 1982). Hospital advertising has increased markedly in recent years and is concentrated in television and print[13] mediums. MHSs have been shown to advertise more than stand-alone hospitals (Huppertz et al., 2017). Although observable measures of hospital quality do not seem to correlate with advertising levels, higher levels of advertising are associated with higher occupancy rates, suggesting an impact on patients' choices (Ndumele et al., 2021).

Hospital-Insurer Bargaining

Starting with Capps et al., 2003, discrete choice methods have been used to measure market power in option-demand markets. Although option-demand models have primarily been studied within the empirical context of healthcare, applications to other industries exist, such as television channel bundling (Crawford and Yurukoglu, 2012). The initial option-demand framework of Capps et al., 2003 has been expanded to encompass additional market details. Ho and Lee, 2017 and Ho and Lee, 2019 more explicitly model hospital-insurer negotiations. Lewis and Pflum, 2015 use hospital cost data to relax the assumption that hospitals have homogeneous Nash bargaining weights. Gowrisankaran et al., 2015 use claims data on the actual prices patients pay at each hospital to incorporate a role for consumer price sensitivity at the time of choosing a hospital. These models treat hospitals as differentiated products, whereas previously popular ad-hoc methods of mea-

[13]This includes newspaper, magazines, and outdoor advertisements.

suring market power treat them as homogeneous. Structural methods have been shown to yield estimates of market boundaries that are less geographically dispersed than alternative methods (Gaynor et al., 2013).

A commonality in each of the variations of this model is that patients are assumed to perfectly perceive what is relevant to their choice problem and, therefore, choose hospitals from the set of all available options. However, Salampessy et al., 2022 find by combining pre-choice hypothetical surveys with actual real-life choices that patients make hospital choices that do not follow their stated preferences. They provide evidence that patients highly value quality information, but that choices do not reflect this. Instead, patients in their sample weight distance traveled much more heavily in actual choices than in stated preferences. This result could be rationalized by patients not being attentive to all available hospitals when faced with the decision.

Consistent with this, different policy interventions that provide information to patients have been studied previously and have been shown to significantly impact demand and increase the quality of chosen hospitals in different contexts (Cutler et al., 2004; Dranove et al., 2003; Pope, 2009). A significant response to an information intervention is at odds with assumptions made in existing structural demand models used to model price formation in hospital markets. This paper seeks to address this apparent contradiction between the empirical evidence and the prevailing modeling assumptions on patient behavior.

In Raval et al., 2022, the authors utilize hospital closures due to natural disasters as a natural experiment to test the ability of various hospital choice models to accurately recover diversion ratios. They find that across all standard specifications, the models underpredict large diversions. In other words, if two hospitals are close substitutes, existing models tend to underpredict this substitutability. The authors show that allowing for unobserved willingness-to-travel through a random coefficient on distance improves model performance by 20-25%.[14] This paper suggests that patients' limited consideration may further explain this observed pattern of bias. Appendix D provides details on the differences in substitution patterns able to be generated by a random coefficient and a random

[14] They evaluate model performance based on the slope of the linear best-fit line of the prediction error (predicted minus observed diversion ratio) on the observed diversion ratio. Adding a random coefficient on distance decreases the slope by 20-25%.

consideration sets model resulting from more general forms of unobserved heterogeneity across options.

Merger Simulation

The diversion ratio is an input into multiproduct firms' Bertrand pricing first-order conditions, with higher within-firm diversion being associated with a greater ability to internalize substitution. Proposition 1 in this paper shows that the prices a multiproduct firm obtains in negotiated price markets can also be written as a function of choice-removal diversion ratios.[15] Thus, bias in diversion estimates imply that counterfactual predictions from merger simulations will also be biased.

This corroborates the existing conflicting evidence of structural methods' accuracy in predicting the anti-competitive effects of hospital mergers. Two earlier papers, Fournier and Gai, 2007 and May and Noether, 2014, find mixed results in a combined sample of 4 realized hospital mergers. Using a larger, nationally represented sample of 28 mergers in Garmon, 2017, the author finds that WTP-based merger screens perform better in comparison to ad-hoc methods based on aggregate patient flows. However, false predictions are still prevalent in the sample of mergers used by Garmon, 2017. Of the 14 mergers flagged for having a predicted increase in WTP of 6% of more, only 7 have an observed statistically significant price increase relative to controls. Additionally, 2 mergers were not predicted to have a significant increase in WTP, but have observed statistically significant price increases. Garmon, 2017 also finds that a full WTP-based merger simulation relating changes in WTP to changes in price yield worse results.

These mixed results are contrary to results from Monte Carlo simulations in Balan and Brand, 2023. In Balan and Brand, 2023, the authors simulate data from a rich theoretical model of hospital-insurer bargaining that is taken to be the "true" model. Then, from the "true" model they simulate mergers using a simplified model that uses only data that is readily available to antitrust authorities in practice. Their results imply that the simplified model is capable of accurately predicting changes in the "true" model. Taken together with other results, this leads one to believe that if the results from an empirical model do

[15] The choice-removal diversion ratio from hospital A to hospital B measures the probability of choosing B if A is removed, conditional on choosing A prior to its removal.

not match the realized price effects, then the real world may deviate in some way from the specified "true" model in Balan and Brand, 2023. This paper provides evidence that erroneous demand assumptions can bias merger simulation results.

Within the broader IO literature focused on applications to non-hospital markets, studies assessing the ability for merger simulation models to accurately predict the price effects of retrospective mergers have generated similarly mixed results. In the seminal paper of Nevo, 2000, merger simulations in the RTE cereal industry paper closely match observed price changes. Similarly, Bjornerstedt and Verboven, 2016 find that merger simulation predictions closely match the aggregate price effects of a merger between two producers of Swedish painkillers. However, the simulation results from Peters, 2006, Weinberg, 2011, and Weinberg and Hosken, 2013 fail to accurately predict prices. The results in this paper concur with Houde, 2012, who shows that vertical mergers in gasoline markets are more accurately predicted when more precise measures of spatial differentiation amongst firms are used. The current paper more precisely measures spatial differentiation by incorporating the influence of distance on both consideration and preferences.

Random Consideration Sets

Manski, 1977 first proposed modeling decision processes in a two-stage framework where the first stage determines whether each product is in a decision maker's consideration set, and the second stage determines choice conditional upon the consideration set realization. There are two statistical models of consideration set formation commonly used in applied literature. First, the default-specific consideration (DSC) model assumes that each decision maker has a default option considered with probability one. The decision maker randomly considers either all available options or only the default option. Previous work has used the DSC model to distinguish between switching costs in utility and inattention in determining decision makers' propensities to choose the same alternatives over time in markets such as residential electricity (Hortacsu et al., 2017) and prescription drug insurance (Ho et al., 2017, Heiss et al., 2012). Previous work has found significant inertia in hospital choice as well (Raval and Rosenbaum, 2018), but this inertia has yet to be decomposed into factors stemming from both utility and attention. This paper uses a short panel of hospital choices such that it is impossible to infer patients' inertial decisions over a long period of time.

This paper uses the other commonly specified consideration set model in the applied literature: the alternative-specific consideration (ASC) model. Within this model, each non-default alternative has a consideration probability that is independent across alternatives, conditional upon observable characteristics.[16] In understanding how limited consideration affects choices, an ASC model of demand refrains from specifying the more detailed aspects of how consideration sets form (i.e., the searching process).[17] This reduced-form probabilistic approximation allows for flexibility in the mechanisms by which consumers form consideration sets. This flexibility is desirable in this paper because it allows for straightforward analytical expressions of firms' advertising first-order conditions.

Moreover, features of hospital markets point to random consideration as a reasonable approximation of patient behavior. In reality, patients face uncertainty not only on the quality of available alternatives but also on the details of the realization of their health shocks. Patients decide on a health care provider in part to reduce the uncertainty that persists about what is wrong with their health. The value of information is not usually known to patients at the time of choosing a hospital (Arrow, 1963), so that micro-foundations of consideration sets based on optimally acquiring information (Caplin et al., 2019) may not accurately describe patient behavior. Moraga-Gonzalez et al., 2024 show that this paper's ASC model is equivalent to a non-sequential search model where decision makers put zero weight on expected utility when searching.

Within this two-stage consider-then-choose model, a patient may not choose a hospital h due to either (i) not considering h or (ii) not preferring h to other considered alternatives. Identification of the ASC model requires distinguishing between these two possibilities.

[16]Similar to in the DSC model, the ASC model assumes each decision maker has some exogenously given default alternative that is considered with probability one. This is to make the model well-defined such that the consideration set is never empty. Horan, 2019 examines how to specify a consideration sets model with unobserved default choices (i.e., choosing to not go to a hospital conditional on having a health shock). In this paper, I maintain that each patient always goes to the hospital if they have a health shock requiring inpatient care and considers the geographically closest feasible option with probability one. Studying the implications of relaxing this assumption is left for future work.

[17]Identifying search costs in a consideration sets model generally requires search data. Previous work has used auxiliary data on consumer search behavior to augment the approach used in this paper's demand model (e.g., Honka, 2014, Honka et al., 2017, De Los Santos et al., 2012).

The most common way to identify consideration probabilities is to exclude variable(s) from either the attention or utility functions, typically with the excluded variables having large support. Recent work shows conditions exploiting theoretical restrictions such that an exclusion restriction is unnecessary for identification. Abaluck and Adams-Pressl, 2021 utilizes asymmetric cross derivatives, and Kashaev et al., 2023 utilizes variation in the choices of peers. Additionally, the literature in behavioral decision theory uses full variation in feasible choice sets for identification (Manzini and Mariotti, 2014) and this has been applied experimentally by Aguiar et al., 2023. Advertising is maintained as an exclusion restriction in this paper to simplify the supply side. Reduced-form evidence in Section 4 supports the validity of this modeling assumption.

This paper builds on previous literature that estimates demand with advertising playing a role in consideration set formation but being excluded from utility (Draganska and Klapper, 2011; Dressler and Weiergraeber, 2023; Sovinsky Goeree, 2008). More generally, this exclusion restriction approach is widely used in the broader literature on identification of finite mixture models (Compiani and Kitamura, 2016). Other applications exploit exogenous changes in the decision-making environment to identify the model without exclusion restrictions. Kawaguchi et al., 2021 and Conlon and Mortimer, 2013 use stock-outs in vending machines as an exogenous source of menu variation. In an application to hospital choice in the context of the demand for a specific surgical procedure, Gaynor et al., 2016 exploits a policy change in England's National Health Service (NHS) which removes latent administrative restrictions on patient's choice sets. Gaynor et al., 2016 finds that moving from a setting where physicians must refer patients to predetermined hospitals to a setting where patients essentially have free choice increases hospitals' incentives to invest in quality.

Testing the superiority of random consideration models compared to full consideration random utility models in describing consumer behavior has proven difficult. In existing work, tests require either experimentally-derived data with full variation in choice sets (Aguiar et al., 2023) or choice data augmented with survey data on decision makers' actual consideration sets (Van Nierop et al., 2010). Aguiar et al., 2023 design an online experiment that varies choice sets and consideration costs to test the accuracy of limited consideration models at the population level compared to full consideration models. They find that a full consideration model is unable to explain the data, whereas their limited consideration model accurately recovers preferences regardless of the difficulty of consideration. Van Nierop et al., 2010 also find convincing evidence that estimated probabilities of consideration from an ASC are strongly correlated with surveyed responses. Unlike existing work which seeks to directly test how accurately the model recovers unobserved consideration, this paper uses a model of price formation to test the choice model's predictive accuracy in determining counterfactual price changes.

Competition for Consideration

Previous empirical applications of the ASC model to consumer choice take the supply side as given and provide choice estimates conditional upon ownership, pricing, and other firm decisions (i.e., advertising) being held constant. This has prevented the existing literature from evaluating counterfactual market interventions due to the need for endogenizing firms' choices. For example, in Sovinsky Goeree, 2008, firms simultaneously post prices and make advertising decisions to maximize profit such that any merger simulation would have to account for interdependent changes in the incentives for each of these decisions.[18] This difficulty is overcome by relying on how prices are formed in the hospital industry. In doing so, this paper departs from existing applications of the ASC model by tractably modeling how market counterfactuals affect equilibrium advertising, the distribution of consideration sets across consumers, and equilibrium prices.

In related theoretical work, Eliaz and Spiegler, 2011 conceptualize advertising as a tool to persuade consumers to consider a firm's products. The authors ask how firms' payoffs relate to a rational consumer benchmark. In their theoretical framework as well as this paper's structural model, firms competitively advertise in order to manipulate consumers' perception of the set of feasible alternatives, but marketing strategies cannot affect consumer preferences. Eliaz and Spiegler, 2011 show that in a homogeneous duopoly where firms compete for consideration, under general conditions on the independence of messag-

[18]Murry, 2017 tractably models the pricing and advertising decisions of automobile manufacturers and retailers in a two-stage game by expressing the retailer's decisions as a function of the maufacturer's along with exploiting novel instruments. Murry, 2017 differs from the current paper by using a full consideration model where advertising enters indirect utility.

ing in separate advertisements, every symmetric Nash equilibrium includes equilibrium profits that are identical to a rational consumer benchmark. However, the boundedly rational equilibria are still Pareto inferior to a counterfactual of rational consumers, because consumers are strictly worse off.

Unlike Eliaz and Spiegler, 2011, this paper's structural model allows for asymmetric interactions amongst hospitals and preference heterogeneity across patients. In the current paper's counterfactuals, results imply that advertising competition's effect on firm prices does not exactly counteract the market segmentation associated with consumers' limited consideration. Armstrong and Vickers, 2022 show theoretically that in settings where consumers are exogenously aware of a subset of options, allowing for asymmetric competition matters when examining comparative statics from changes in ownership. Though the models differ considerably, this paper follows Armstrong and Vickers, 2022 in giving mergers a set-theoretic interpretation where merger-induced price changes depend on the overlap in consideration sets amongst consumers.

If limited consideration impacts prices relative to a full consideration benchmark, then this may perpetuate misalignment in incentives between insurers and patients. Behavioral hazard is defined as "misbehavior resulting from mistakes or behavioral biases, rather than privately optimal but socially suboptimal choices resulting from misaligned incentives" (Baicker et al., 2015). Baicker et al., 2015 add this concept to a model of healthcare utilization as a parallel to moral hazard, and show using a field experiment that the welfare effects of lower copays are different in both sign and magnitude from a standard model with only moral hazard.

The current paper effectively takes utilization to be fixed, and the choice studied is which hospital to go to conditional on utilizing care. Within hospital demand, misaligned incentives between insurers and patients may arise if patients choose hospitals that are more expensive than available substitutes of comparable quality. Previous work (Gowrisankaran et al., 2015) has shown that efforts from insurers to realign these incentives by distorting the coinsurance paid by patients at different hospitals are largely ineffective due to patients not responding strongly to price changes at the time of seeking care. This paper adds to the literature on behavioral hazard by showing that conditional upon utilization, patients' behavioral biases can impact welfare assessments, measurement of market power, and counterfactual predictions. Results from counterfactual simulations suggest that a more effective strategy for insurers to push patients towards lower cost hospitals[19] may be to "nudge" patients through the provision of information that makes these hospitals more salient.

Effects of Hospital Advertising

Two related studies explore the interaction of hospital advertising with patients' choices. First, Montefiori, 2008 presents a model where patients' perceived quality is a weighted sum of actual quality and the hospital's advertising efforts. In this framework, hospitals are incentivized to invest more in advertising than in quality improvements, which take longer to realize. They suggest that providing patients with more information about hospital quality could shift the focus from advertising to actual quality. The current paper builds on this by estimating the potential benefits of insurers providing better information, reflected in the compensating variation estimates from the full consideration counterfactual.

Second, Kim and Diwas, 2020 combines patient-level hospital choice data with hospital advertising data, using an instrumental variable design to control for the endogeneity of advertising. Their counterfactual analysis suggests that advertising may help sort patients to higher-quality hospitals. Unlike their approach, which examines fixed hospital choice sets with advertising entering into the utility function, the current paper models advertising as shaping the set of hospitals patients consider. This paper's focus is on how competitive advertising affects patient substitution patterns and the resulting implications for consumer welfare and market power, using revealed preferences and supply estimates to quantify patient welfare in dollar terms.

3 Data

In this section, I first describe the inpatient discharge data used to estimate the demand model. Then, I describe how prices are approximated for both the supply model and for the retrospective merger price regressions. Next, I describe the advertising data.

[19] As will be described in Section 8, hospitals with lower negotiated prices tend to be less salient.

3.1 Inpatient Discharge Data

The primary dataset is from the Pennsylvania Health Care Cost Containment Council (PHC4) and includes information on all privately insured inpatient discharges from Philadelphia County acute care hospitals from 2017Q3-2018Q2 and 2022Q3-2023Q2. The data includes information regarding the clinical, demographic, and insurance plan characteristics of patients, as well as hospital identifiers and characteristics. I obtain information on the ownership of hospitals, along with the dates of any changes in ownership, from the American Hospital Directory.

The data includes 99 unique plan identifiers, with 82 being present in the first year and 72 in the second year. The plans vary widely in the number of observations in the data: 91.6% of patient discharges come from plan-years with over 1,000 observed discharges, but these account for only 24 of the 154 plan-years. Figure 1 below displays a map of all acute care hospitals in the final cleaned data along with the systems of ownership.[20]

[20] A limitation of the data is that hospital visits in neighboring counties are unobserved, which requires modeling the choice as conditional upon going to an acute care hospital in Philadelphia County.

Figure 1: Map of Acute Care Hospitals in Philadelphia County, 2018

The structural model requires approximating the feasible set of in-network options that plan enrollees have available to them. This approximation is begun under an implicit assumption that all in-network options are chosen at least once by a plan enrollee throughout the year. Several issues arise with this approximation strategy that require additional simplifications. First, not all plan IDs are available. To solve this, each individual with an unavailable plan ID is assumed to have the most commonly observed plan identifier, within the same listed type of plan, in their zip code. As seen in the Summary Statistics in Table 1, plans are grouped into 11 different types based on type of coverage (EPO, PPO, POS, FFS, HMO) and type of ownership (Blue Cross or Other Commercial).

A second issue is that some plans have such few observations that the network cannot accurately be backed out. Each plan-year with less than 1,000 observations is assumed to have a network identical to the most commonly observed plan of the same type in the respective year. For plans with unknown types and plan-types with no plans having over 1,000 observations, networks are assumed to be identical to the most commonly observed network. In total, there are 15 unique network configurations for the 2018 fiscal year, which is the year for which the structural model is to be estimated.

Next, any observations missing necessary patient information are excluded. 386 observations are dropped due to zip codes being unavailable, and 7.96% (10,734 total) of observations are dropped due to having all in-network options in the data farther than 60 miles away. Similarly, any in-network option that is over 60 miles away from a remaining patient is removed from that patient's choice set, and will be subsumed into the outside option in the structural model. In the same way, all hospitals with a remaining market share of less than one percent or a within-MDC (major diagnostic category) market share of less than one percent are removed and subsumed into patients' outside options.[21] Only patients younger than 65 years old are included to prevent counting any patients concurrently enrolled in Medicare. Any discharges related to newborns and neonatal care are excluded to prevent double counting. Finally, childrens' hospitals are removed from patients' choice sets if they are over 19 years old. In the final sample used for the structural analysis, there are 54,528 unique observations of patient visits, 17 hospitals including the outside option, and 97.31% of patients choose an inside option. Summary statistics for patients' diagnosis categories are in Appendix K.

[21]The utility of the outside option is normalized to zero in the structural model. For the outside option's attention function, distance is assumed to be 60 miles.

Table 1: Patient Summary Statistics, 2017-2018

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Age	54,528	39	19	0	26	56	64
Insurance Plan Coverage	54,528	0.84	0.19	0.1	0.8	0.95	1
Distance	54,528	14	16	0.12	2.8	21	60
Zip Code Median Income	54,528	64,419	29,398	15,232	41,599	82,712	250,000
Severity Weight	54,528	1.7	1.9	0.49	0.83	1.9	25
I(Non-White)	54,528	0.41	0.49	0	0	1	1
I(Female)	54,528	0.56	0.5	0	0	1	1
Chose Closest Option	54,528	15%					
Type of Coverage	54,528						
... FFS	7,811	14%					
... HMO	16,466	30%					
... POS	3,767	7%					
... PPO	21,773	40%					
... EPO	2	0%					
... Unknown	4,709	9%					
Type of Plan Ownership	54,528						
... Blue Cross	19,170	35%					
... Other Commercial	35,358	65%					

Approximating Prices

For the structural analysis, case-mix adjusted prices negotiated between hospital systems and insurers are approximated by utilizing information on the covered hospital charges in the patient discharge data combined with hospitals' financial information observed in financial reports that are publicly available from PHC4. The financial reports data are used to approximate revenue-to-charge ratios from measures of (i) total net patient revenue from private payers and (ii) total charges attributed to private payers. Hospitals in the final sample are grouped by system, and a system-level ratio is obtained by taking a revenue-weighted average across locations. Then, after obtaining this system-level revenue-to-charge ratio, the financial data is merged with the patient discharge data. The top and bottom one percent of each system-plan's total covered charges in the discharge data are winsorized. Assuming each system's ratio is constant across plans, the derived ratio can approximate in-sample system-plan level average revenue per weighted discharge[22][23].

For the price difference-in-differences regressions used in the natural experiment to measure the realized merger-induced price effects, having a nationwide set of control hospital is essential to obtain an adequate number of observations. For this reason, these regressions use data from the Centers for Medicare & Medicaid Services' (CMS) Healthcare Cost Report Information System (HCRIS). Using the procedure originally introduced by Dafny, 2009, a nationwide set of hospitals' case-mix adjusted prices are approximated. This process is done for one pre-merger year, the fiscal year of 2018, corresponding to the same time period used in the data for the structural model. The merger was initially announced in November of 2018 and approved in December of 2020. Post-treatment prices are approximated for the most recent fiscal year with adequate data coverage, 2022. Each hospital's case-mix index (CMI) from CMS' Impact Files is used to adjust for differences in average severity across hospitals. Each hospital's price for this part of the analysis is measured as

$$\tilde{p}_{ht} = \frac{\left(IPCHARGE_{ht}\right)\left(1 - \frac{CONTDISC_{ht}}{GROSREV_{ht}} - MCRREIMB_{ht}\right)}{\left(DISCH_{ht} - MDISCH_{ht}\right)CMI_{ht}}.$$

$IPCHARGE_{ht}$ are the total inpatient charges. $CONTDISC_{ht}$ are contractual allowances and discounts on patients' accounts and $GROSSREV_h$ denotes the inpatient and outpatient combined total charges. $DISCH_h$ denotes the total number of inpatient discharges and $MDISCH_{ht}$ are the number of Medicare discharges. CMI_{ht} is the case-mix index. In

[22]Following the literature, average revenue per discharge is henceforth referred to as price.

[23]As seen in Table 2 below, two hospitals owned by Jefferson Health do not have Medicare data available. It is believed that this is due to the way Jefferson Health reports revenue: "Under the Medicare provider-based rules it is possible for 'one' hospital to have multiple inpatient campuses..."(CMS, 2024b). Although these locations are described as subsidiaries of Thomas Jefferson University Hospital in the merger case (FTC v. Thomas Jefferson University, 2020), they are treated as distinct locations in the discharge data.

each of the years under study, between 73-75% of hospitals do not have a case-mix index available, including one of the merging firms' flagship locations. To solve this, the case-mix index for each missed observation is replaced with the hospital's case-mix index in the other year, if applicable. For non-treated hospitals without a case-mix index available, the median observable case-mix is assumed whenever necessary.[24]

Table 2: Hospital Summary Statistics, 2017-2018

Hospital	System	Net Patient Revenue ($1,000s)	Medicare Share of Net Patient Revenue	Medicaid Share of Net Patient Revenue	Inpatient Discharges	# Of Inpatient Beds
Einstein Medical Center	Einstein Healthcare Network	660,283	0.4	0.39	25,284	752
Chestnut Hill Hospital	Tower Health	99,105	0.56	0.12	7,436	130
Children's Hospital of Philadelphia	Stand Alone	1,992,740	0.01	0.29	535	535
Hahnemann University Hospital	Paladin Health	413,111	0.36	0.29	6,328	176
Hospital of Fox Chase Cancer Center	Temple U. Health System	366,786	0.33	0.04	4,608	98
Hospital of the U. of Penn.	U. of Penn. Health System	2,750,543	0.28	0.11	21,248	464
Jeanes Hospital	Temple U. Health System	149,270	0.42	0.19	6,328	176
Mercy Philadelphia Hospital	Mercy Health System	146,843	0.29	0.62	7,496	157
Nazareth Hospital	Mercy Health System	148,178	0.44	0.24	6,556	203
Penn Presbyterian Medical Center	U. of Penn. Health System	838,069	0.36	0.15	16,192	305
Pennsylvania Hospital	U. of Penn. Health System	581,128	0.27	0.16	24,044	496
St. Christopher's Hospital for Children	Paladin Health	285,930	0.04	0.66	7,060	189
Temple U. Hospital	Temple U. Health System	1,164,965	0.28	0.43	30,012	721
Thomas Jefferson U. Hospital	Jefferson Health	1,585,561	0.32	0.13	34,892	951
Methodist Hospital	Jefferson Health	NA	NA	NA	6,624	198
Aria Health	Jefferson Health	NA	NA	NA	21248	464

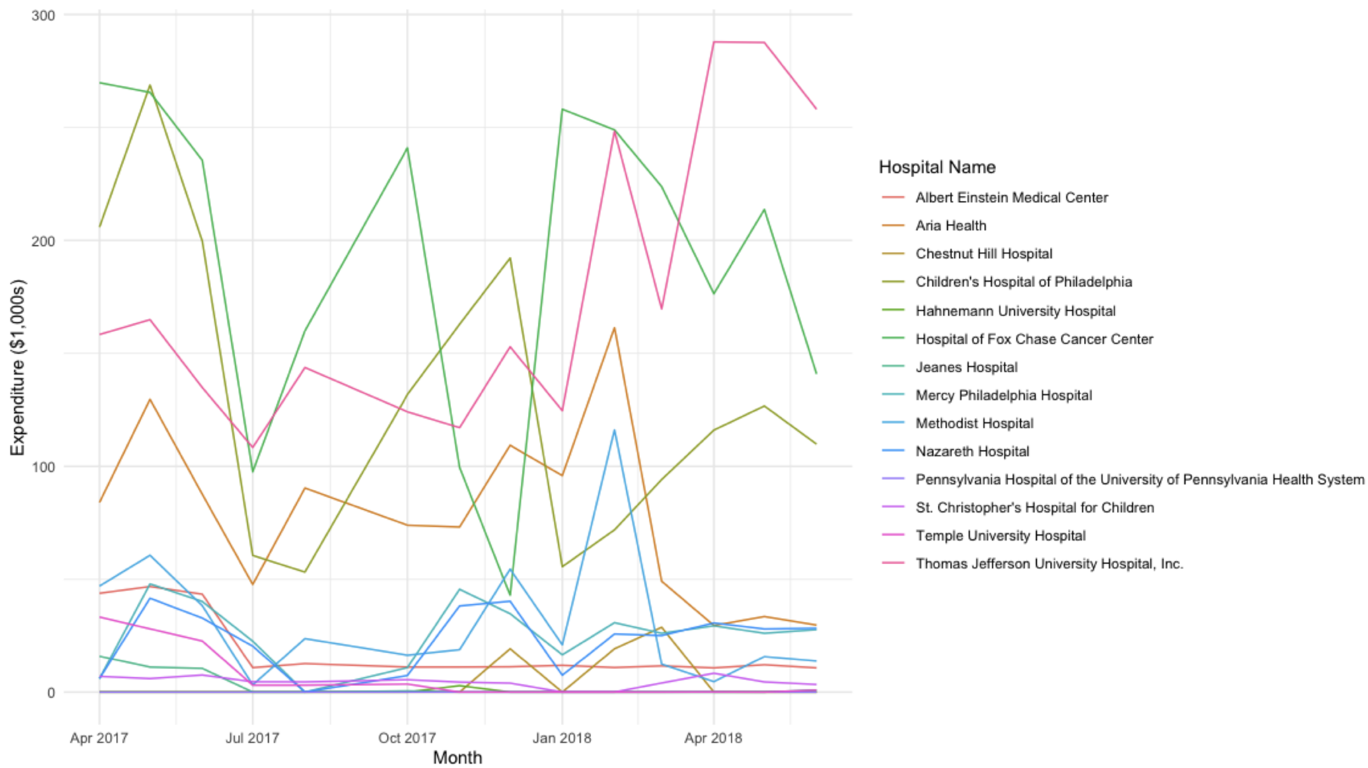
Table 3: Hospital System Summary Statistics, 2017-2018

System	Sample Market Share	Number of Inpatient Beds
Einstein Healthcare Network	0.09	752
Tower Health	0.03	130
Children's Hospital of Philadelphia	0.07	535
Paladin Health	0.09	685
Temple University Health System	0.15	995
University of Pennsylvania Health System	0.28	1590
Mercy Health System of SE Pennsylvania	0.05	360
Jefferson Health	0.23	1613

[24] See Appendix J for robustness checks excluding all observations with any missing values.

Advertising Data

Figure 2: Hospital Monthly Advertising Expenditure



Data on hospitals' monthly advertising expenditures is obtained from Kantar Media's AdSpender Database, which gives firms' monthly advertisement expenditure across mediums in the hospital industry. Kantar tracks advertising frequency and spending for most brands across various industries, spanning national and local television, newspapers, magazines, radio, and outdoor advertising. For the local Philadelphia market, data is taken from the Industry Group "Medical Services and Equipment." Then, the data is subset to two subcategories: "Hospitals & Medical Healthcare Systems" and "Hospitals, Clinics, and Medical Centers Corporate Promotion/Sponsorship,"[25] Next, I classify by ownership based on the most detailed classification in the data, "Brand."

[25] Additionally, for a in-sample hospital specializing in cancer services, the subcategory "Cancer Clinics/Associations" is used.

It is common for hospital systems in the data to jointly advertise their multiple locations. A similar pattern of group advertising has been observed in the personal computer industry by Sovinsky Goeree, 2008. I follow this paper in modeling each hospital's "effective" expenditure by adding up the total advertising within each group the hospital is a part of and weighing each group based on the group's number of in-sample hospitals. Let $\mathbf{G}_h$ denote the set of all advertising groups consisting of hospital h. In the data, each hospital either advertises alone or with every other hospital from within their system. Let $\tilde{a}_{gt}$ be the observed advertising expenditure of group g in month t. Group g's average expenditure per product is $\overline{a}_{gt} = \frac{\tilde{a}_{gt}}{|g|}$. Then, the effective advertising expenditure for hospital h is[26]

$$a_{ht} = \sum_{g \in \mathbf{G}_h} \overline{a}_{gt}.$$

In previous literature, advertising stock, which is denoted as $\mathbf{a}_{ht}$, is specified as the discounted sum of the log-transformation of current and lagged advertising, where a carryover parameter to the power of the number of lags discounts previous periods' advertising (Dube et al., 2005; Kim and Diwas, 2020). Given the relatively short sample, there is concern about insufficient variation in advertising stocks over time if many months' lags are used. Additionally, in the Philadelphia data, admission timing is only observed at a quarterly frequency such that expenditure is aggregated from a monthly to quarterly frequency. For these reasons, only the current quarter's logged transformation of expenditure is used to measure advertising stock. As to be discussed in Section 4, the current quarter's logged advertising expenditure significantly affects demand in the aggregate. This helps to validate the following specification for advertising stock:

$$\mathbf{a}_{ht} = \ln(1 + a_{ht}).$$

[26] Sovinsky Goeree, 2008 also includes a separable squared term in this equation and estimates the weight on each of the terms to allow for either increasing or decreasing returns to scale for group advertising. I refrain from doing so in this paper due to limited variation in the sizes of groups. Therefore, this paper assumes constant returns to group advertising.

4 Reduced-Form Evidence

This section provides reduced-form evidence that advertising expenditure significantly affects hospital demand in a manner consistent with informative advertising. Ackerberg, 2001 introduces a test for the presence of informative and/or prestige advertising on demand by comparing the responses to advertising for experienced and inexperienced consumers. Informative advertising should not play a role amongst consumers already familiar with a firm's brand. In contrast, prestige advertising should because the brand image can still provide these consumers with additional satisfaction. Both informative and prestige advertising should affect consumers who are ex-ante unfamiliar with a firm's brand. Therefore, one can examine the difference in the effectiveness of advertising for a firm's experienced and inexperienced consumers to disentangle the informative from the prestige effects of advertising. If consumers respond to advertising when unfamiliar with a firm's brand but do not respond when familiar, then this would suggest advertising primarily acts to inform.

In applying a similar test to the data, using previous visits as a proxy for hospital brand familiarity would be troublesome due to an initial conditions problem: a short panel of hospitals is observed in a stable market with little entry and exit.[27] There is not enough information to accurately tell which patients are familiar with which hospitals from observed previous visits. Instead, the reduced-form analysis utilizes the fact that many hospitals are part of multi-product firms with various locations throughout the region.

As an illustrative example, consider a market that includes three hospitals: h_1, h_2, and h_3. Suppose the three hospitals are identical, except they are in different geographic locations. Hospital system s owns both locations h_1 and h_2. Suppose a patient lives one mile from h_1 and lives 20 miles from both h_2 and the non-system hospital h_3. In this case, the patient will likely be familiar with the brand of s due to proximity to h_1. Informative advertising would lead to the marginal effect of advertising on this patient's choice probability for h_3 to be much larger than for h_2. Prestige advertising would suggest that the response of advertising for h_2 and h_3 should be identical for this patient.

Multiple reduced-form specifications are used to test this intuition and to motivate the

[27]The original test proposed by Ackerberg, 2001 uses data on a newly introduced yogurt product.

assumptions made in the structural model. Patients are grouped by zip code and the within-zip market share is taken for each hospital every quarter. Then, zip-quarters with less than 50 total discharges are removed. Table 4 below provides initial evidence that advertising significantly affects demand and that its impact is increasing in a zip code's geographic distance from the hospital. This positive relationship is robust to multiple specifications. Columns (1)-(3) use OLS, whereas Columns (4)-(6) account for the potential for advertising to be endogenous and controls for it in a first stage using Hausman-type instruments, the details of which are discussed in Section 6.2.[28] Additionally, each specification controls for vertical product differentiation by including hospital fixed effects.

Table 4: Impact of Advertising on Market Shares

	Mkt. Shr.$_{zht}$					
		OLS			*2SLS*	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(1+a_{ht})$	0.834***	0.797***	0.448***	0.963***	0.915***	0.562***
	(0.082)	(0.082)	(0.099)	(0.110)	(0.111)	(0.128)
Distance$_{zh}$		−0.064***	−0.131***		−0.063***	−0.129***
		(0.011)	(0.015)		(0.011)	(0.016)
$\ln(1+a_{ht}) \times$ Distance$_{zh}$			0.026***			0.025***
			(0.004)			(0.004)
Observations	6,363	6,363	6,363	6,363	6,363	6,363
R^2	0.378	0.381	0.385			
Notes: OLS, Hospital FEs included.						

In what follows, the instrumental variable specification in Column (6) is used as a baseline and additional variables of interest are added. The corresponding OLS results are in Appendix E. Specifications are ran with new terms involving an indicator variable for whether another commonly-owned hospital exists within 5, 10, and 15 miles of the zip code. In the example above with system s, the indicator for h_2 would be set to 1 because

[28] Specifically, lagged log advertising expenditure and its interaction with distance are included as instruments

the commonly owned h_1 is near the patient's residence. However, in this situation, the nearby h_1 would have the indicator set to zero. The signs of each variable included in Table 4 are robust to the inclusion of additional variables in Table 5. Results show that having a nearby hospital reduces the effectiveness of advertising for commonly-owned locations farther away. Patients in areas where residents are more likely to have prior knowledge of a particular hospital's brand appear to have their behavior significantly less strongly affected by that hospital's advertising relative to other patients located throughout the county, conditional upon controls. The results from this section, along with the initial motivations for allowing medical advertising described in Section 2, prompt the modeling assumption that advertising affects consideration, but not utility.

Table 5: Varying Impact of Advertising On Market Shares Depending on Prior Brand Familiarity

	Mkt. Shr.$_{zht}$		
	(1)	(2)	(3)
ln(1+a$_{ht}$)	0.665***	0.614***	0.548***
	(0.131)	(0.130)	(0.129)
Distance$_{zh}$	-0.129^{***}	-0.129^{***}	-0.126^{***}
	(0.016)	(0.016)	(0.016)
ln(1+a$_{ht}$) $\times$ Distance$_{zh}$	0.024***	0.027***	0.028***
	(0.004)	(0.004)	(0.004)
I(System Hospital $<$ 5 Miles)$_{zh}$	0.018		
	(0.653)		
I(System Hospital $<$ 10 Miles)$_{zh}$		-1.428^{**}	
		(0.650)	
I(System Hospital $<$ 15 Miles)$_{zh}$			-1.319^{*}
			(0.754)
ln(1+a$_{ht}$) $\times$ I(System Hospital $<$ 5 Miles)$_{zh}$	-0.967^{***}		
	(0.179)		
ln(1+a$_{ht}$) $\times$ I(System Hospital $<$ 10 Miles)$_{zh}$		-0.630^{***}	
		(0.156)	
ln(1+a$_{ht}$) $\times$ I(System Hospital $<$ 15 Miles)$_{zh}$			-0.419^{**}
			(0.184)
Observations	6,363	6,363	6,363

Note: 2SLS, Hospital FEs included

5 Structural Model

$\mathbf{H}$ denotes the set of all hospitals indexed by $h = 1, ..., H$. Hospitals are separated by ownership into $\mathbf{S}$ systems, indexed by $s = 1, ..., S$. $\mathbf{H_s}$ denotes the set of hospitals in system s. $\mathbf{M}$ denotes the set of all insurance plans indexed by $m = 1, ..., M$. Each m has a fixed set of in-network hospitals $\mathbf{H}_m \subset \mathbf{H}$. Insurance plans have a combined set of enrollees indexed by $i = 1, ..., I$ where each i's insurer $m(i)$ is taken to be fixed. Each quarter, each patient i receives a health status draw determining if she needs inpatient care. $\mathbf{I_t}$ denotes the set of all consumers sufficiently ill to require inpatient care in period t, with $N_t = |\mathbf{I_t}|$. $\mathbf{I_{m,t}}$ and $N_{m,t}$ denote the corresponding measures specific to insurance plan m's enrollees. $g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{ht}})$ is the joint density of patient clinical characteristics $\mathbf{z_t}$, patient demographics $\mathbf{k_t}$, and hospital marginal costs of advertising $\mathbf{f_{ht}}$ for all $i \in \mathbf{I_t}$ and $h \in \mathbf{H}$ and with finite support $Z \times K \times F$. Health shocks are independent of the realization of hospitals' marginal costs such that $g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{ht}}) = g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) g_f(\mathbf{f_{ht}})$. Denote $g_z(\mathbf{z_{it}}|\mathbf{k_{it}})$ as the conditional density of clinical characteristics for a patient with demographics $\mathbf{k_{it}}$.

5.1 Demand Model

The demand model is agnostic to the specific mechanisms by which consideration sets may form. Rather, a reduced-form approach is taken in measuring the marginal effects of observable characteristics on the independent probability of each hospital being included within each patient's set of products to be chosen from. Each patient, given her fixed health insurance plan, receives a health draw each period which may require inpatient hospital care. If a patient requires inpatient care, then she randomly considers a possibly limited set of in-network hospitals from her managed care insurer's (MCO) network. Given the realized set of hospitals, patients choose the one yielding the highest utility.

Consideration

Fix some insurance plan $m \in \mathbf{M}$. Conditional on receiving a health shock requiring inpatient hospital care, each patient $i \in \mathbf{I_{m,t}} \subset \mathbf{I_t}$ forms a consideration set of hospitals to choose from. The consideration set is a subset of the feasible set made up of all $h \in$

$\mathbf{H}_m$. Denote the probability that i considers hospital j upon falling ill in quarter t as $\phi_{ijt}(\mathbf{v_{ijt}})$ where $\mathbf{v_{ijt}}$ is a vector of consideration shifting variables. For all $j \in \mathbf{H}_m$, the probability of considering a hospital is influenced by its advertising, other hospital-specific characteristics, and the individual's clinical and demographic attributes. Let $\mathbf{C_i}$ denote the power set of hospitals available to individual i. The consideration set probabilities take the following form $\forall c \in \mathbf{C_i}$

$$pr_{it}(c|\mathbf{v_{it}}) = \prod_{j \in c} \phi_{ijt}(\mathbf{v_{ijt}}) \prod_{j' \notin c} (1 - \phi_{ij't}(\mathbf{v_{ij't}})), \tag{1}$$

where $\mathbf{v_{it}} = [\mathbf{v_{i0t}}, ..., \mathbf{v_{ijt}}, ..., \mathbf{v_{iHt}}]$. $\phi_{ijt}(\mathbf{v_{ijt}})$ in (1) is assumed to take the logit form:

$$\phi_{ijt}(\mathbf{v_{ijt}}) = \frac{exp(\mathbf{v_{ijt}}\tau)}{1 + exp(\mathbf{v_{ijt}}\tau)},$$

and τ is a vector of parameters. Equivalently, $i's$ attention function towards h can be denoted as

$$A(\mathbf{v_{iht}}) = \mathbf{v_{iht}}\tau - \eta_{iht},$$

where η_{iht} is an i.i.d. consideration shock following the type-1 generalized extreme value distribution (EV-1). Assumption 1D formalizes the requirements imposed on the error terms in the utility and attention functions.

Assumption 1D. $\forall i \in \mathbf{I_t}$, $h \in \mathbf{H}$, *and* $t \in \mathbf{T}$, $\eta_{iht} \sim$ *EV-1 and* $\eta_{iht} \perp \eta_{ih't}$ *if* $h' \neq h$.

Patient i includes h in her consideration set if and only if $A(\mathbf{v_{iht}}) > 0$. To ensure that each realized consideration set is non-empty, each individual's default alternative to be considered with probability one is taken to be the geographically closest hospital from within the feasible set of in-network options.

Assumption 2D. $\forall t \in \mathbf{T}$ *and* $i \in \mathbf{I_t}$, *i considers the geographically closest hospital with probability one.*

Utility

After realizing c, i chooses to maximize utility amongst all the considered hospitals. Patient i's preferences for hospital h in quarter t are based on the following random utility model:

$$u_{iht}(\mathbf{x_{iht}}) = \mathbf{x_{iht}}\beta + \varepsilon_{iht}, \tag{2}$$

where $\mathbf{x_{iht}}$ is a vector of utility shifting hospital and individual characteristics, β is a vector of parameters, and ε_{iht} is an i.i.d. EV-1 taste shock independent of the consideration shock.

Assumption 3D. *$\forall i \in \mathbf{I_t}$, $h \in \mathbf{H}$, and $t \in \mathbf{T}$, $\varepsilon_{iht} \sim$ EV-1, $\varepsilon_{iht} \perp \varepsilon_{ih't}$ if $h' \neq h$, and $\varepsilon_{iht} \perp \eta_{iht}$.*

The choice variable y_{iht} is equal to one if h is in i's realized consideration set c and i prefers h to every other option within c. Given the distributional assumption on ε_{iht}, the probability that i chooses h conditional upon the realization of c is

$$s_{iht}(\mathbf{x_{it}}|c) = \mathbf{I}(h \in c)\frac{exp\left(\mathbf{x_{iht}}\beta\right)}{\sum\limits_{j\in c} exp\left(\mathbf{x_{ijt}}\beta\right)}, \tag{3}$$

where $\mathbf{x_{it}} = [\mathbf{x_{i0t}}, ..., \mathbf{x_{ikt}}, ..., \mathbf{x_{iHt}}]$. The unconditional choice probabilities observed from the data are

$$s_{iht}(\mathbf{x_{it}}, \mathbf{v_{it}}) = \sum_{c\in\mathbf{C}_{i,h}} pr_{it}\left(c|\mathbf{v_{it}}\right) s_{iht}(\mathbf{x_{it}}|c), \tag{4}$$

where $\mathbf{C}_{i,h}$ denotes the set of all $c \in \mathbf{C_i}$ with $h \in c$.

Willingness-To-Pay

The expected utility to i conditional on the realized vector $\mathbf{x_{it}}$ is

$$\mathbb{E}[\max_{k\in\mathbf{H}_m} u_{ikt}(\mathbf{x_{ikt}})] = \sum_{c\in\mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}})\mathbb{E}\left(\max_{k'\in c} u_{ik't}(\mathbf{x_{ik't}})\right) = \sum_{c\in\mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \ln\left(\sum_{k'\in c} exp(\mathbf{x_{ik't}}\beta)\right) + d,$$

where d is an arbitrary constant. Capps et al., 2003 refer to $\mathbb{E}[\max_{k \in \mathbf{H}_m} u_{ikt}(\mathbf{x_{ikt}})] - \mathbb{E}[\max_{k' \in \mathbf{H}_m \setminus \mathbf{H_s}} u_{ik't}(\mathbf{x_{ik't}})]$ as i's willingness-to-pay to have the hospitals within system s included in the network $\mathbf{N}_m$. Normalizing by the marginal utility of income α_i,[29] this is denoted as

$$WTP_{it}\left(\mathbf{H_s}|\mathbf{H_m}\mathbf{x_{it}},\mathbf{v_{it}}\right) = \frac{1}{\alpha_i}\sum_{c \in \mathbf{C_i}} pr_{it}\left(c|\mathbf{v_{it}}\right)\left[\ln\left(\sum_{k \in c} exp(\mathbf{x_{ikt}}\beta)\right) - \ln\left(\sum_{k' \in c_{\setminus\{\mathbf{H_s}\}}} exp(\mathbf{x_{ik't}}\beta)\right)\right]$$

$$= \frac{1}{\alpha_i}\sum_{c \in \mathbf{C_i}} pr_{it}\left(c|\mathbf{v_{it}}\right)\ln\left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}\left(\mathbf{x_{it}}|c\right)}\right), \tag{5}$$

where the set $c_{\setminus\{\mathbf{H_s}\}}$ consists of the hospitals in c but excluding those affiliated with system s. Note that Equation (5) is expressed as allowing i to still counterfactually consider some h' even if h' can no longer be chosen due to being out-of-network. Patient i's willingness-to-pay to include $\mathbf{H_s}$ in her network prior to clinical characteristics and firms' advertising costs being realized is

$$WTP_{it}\left(\mathbf{H_s}|\mathbf{H_m}\right) = \int_{Z,F} \frac{1}{\alpha_i}\sum_{c \in \mathbf{C_i}} pr_{it}\left(c|\mathbf{v_{it}}\right)\ln\left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}\left(\mathbf{x_{it}}|c\right)}\right) g_f(\mathbf{f_{ht}}) g_z(\mathbf{z_{it}}|\mathbf{k_{it}}) d\mathbf{f_{ht}} d\mathbf{z_{it}}.$$

Summing over all $i \in \mathbf{I_{m,t}}$ and all quarters $t \in \mathbf{T}$ for which a contract is negotiated:

$$WTP_m\left(\mathbf{H_s}|\mathbf{H_m}\right) = \sum_{t \in \mathbf{T}} N_{mt} \int_{Z,K,F} \frac{1}{\alpha_i}\sum_{c \in \mathbf{C_i}} pr_{it}\left(c|\mathbf{v_{it}}\right)\ln\left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}\left(\mathbf{x_{it}}|c\right)}\right) g_{zkf}(\mathbf{z_{it}},\mathbf{k_{it}},\mathbf{f_{ht}}) d\mathbf{f_{ht}} d\mathbf{k_{it}} d\mathbf{z_{it}}. \tag{6}$$

Equation (6) gives the increase in expected utility the hospitals $h \in \mathbf{H_s}$ provide to all potential patients enrolled in plan m at the time of contract negotiation. Next, Equation (7)

[29] Empirically, α_i is taken to be constant across individuals.

takes the sum of (6) over all $m \in \mathbf{M}$:

$$WTP(\mathbf{H_s}) = \sum_{t \in \mathbf{T}} \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K,F} \frac{1}{\alpha_i} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \ln\left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c)}\right) g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}. \tag{7}$$

Proposition 1 in Appendix A shows that the willingness-to-pay to include a multi-hospital system can be expressed as a function of the consideration set probabilities, the consideration set-specific willingness-to-pay for any considered system hospital, and all consideration set-specific within-firm diversion ratios from this system hospital. This extends previously made connections between diversion ratios and willingness-to-pay for single-product firms in Conlon and Mortimer, 2021. Measuring diversion ratios and joint willingness-to-pay changes have been treated as separate exercises in answering antitrust questions (Farrell et al., 2011). The result in Appendix A shows how the two are closely connected for multi-product firms, with these firms having incentives to advertise in order to increase the substitutability between owned locations in patients' realized consideration sets.

5.2 Supply Model

The model of competition between hospitals and insurers consists of two stages. In the first stage, hospitals negotiate in a Nash-in-Nash bargaining game of complete information (Horn and Wolinsky, 1988) with insurers over prices and network inclusion. The complete information assumption here requires that all parties know the distributions from which patient location, demographic, and clinical characteristics are drawn, as well as the distributions from which hospitals' marginal costs of advertising are drawn. Suppose that at the time of contract negotiations, before any health shocks, cost shocks, or consideration sets are realized, patients collectively have a significant increase in unconditional expected utility from including a hospital in their insurer's network. This leads to the insurer having a low threat point in negotiations and results in higher hospital prices. Each patient's expected utility depends not only on preferences towards the hospital, as is standard, but also its probability of being considered. Hospitals can manipulate consideration through competition in advertising expenditure.

Completing the model requires insurers and hospitals to be bargaining in the first stage conditional upon the expected outcome of the advertising game to be played throughout the negotiated contract. In the second stage, hospitals compete for patients' consideration. At the beginning of each period throughout the contract negotiated in the first stage, marginal costs of advertising are drawn from hospital-specific distributions, hospitals choose advertising expenditure, and patients' health shocks are realized.[30] Equilibrium advertising expenditures affect patients' probabilities of considering different hospitals and, by doing so, change the willingness-to-pay (WTP) for each hospital's inclusion in each insurer's network. This change in WTP is reflected in different prices able to be negotiated in the first stage.

5.2.1 Bargaining Stage

The Nash-in-Nash solution concept of Horn and Wolinsky, 1988 alllows for tractably modeling the division of surplus in negotiations between hospitals and insurers with interdependent payoffs. Each upstream (hospital) and downstream (health insurance) firm negotiate lump sum transfer payments for inclusion in the insurer's network, where the outcome is the Nash bargaining solution. The Nash bargaining solution maximizes the joint surplus, which is a function of the values to each firm from having the contract relative to not reaching an agreement. Each pair negotiates bilaterally, conditional upon all other prices being held fixed. At the time of negotiations, each pair has complete information of the other's payoff. That is, each side recognizes the distribution of health shocks throughout the year amongst the population, as well as the distribution from which marginal costs of advertising are drawn each period.

Assumption 1B. *Each health insurance plan $m \in \mathbf{M}$ negotiates independently with each hospital system $s \in \mathbf{S}$.*

Assumption 2B. *Each system s takes the prices negotiated by every other system $s' \in \mathbf{S}$ as given.*

[30] Advertising cost shocks are assumed to be independent of health shocks.

This solution concept involves numerous Nash bargaining problems nested within a Nash equilibrium encompassing all firms. Collard-Wexler et al., 2019 provide conditions such that the Nash-in-Nash solution is asymptotically equivalent to a unique perfect Bayesian equilibrium with passive beliefs in an infinite-period alternating offers game. In the absence of data on the actual amount paid for each patient visit, coinsurance differences across hospitals, and inpatient visits not covered by insurance, the following additional assumptions must be made:

Assumption 3B. *Negotiated prices do not affect demand.*

Assumption 4B. *There is no demand for out-of-network hospitals.*

Assumption 5B. *Each hospital receives the same share of gains from trade.*

Gowrisankaran et al., 2015 depart from the literature and relax Assumption 3B, finding that patients are still quite price insensitive with an average estimated own-price elasticity of 0.12. Assumption 4B fixes the disagreement point between any hospital and insurer to be zero such that there are no off-contract transactions. The ramifications of relaxing this assumption to allow for out-of-network payments are studied in Prager and Tilipman, 2020. Lewis and Pflum, 2015 relax Assumption 5B and find that multi-hospital systems have higher Nash bargaining weights than stand-alone hospitals. All variation associated with relaxing Assumptions 3B-5B is fixed in order to concentrate on particular mechanisms by which limited consideration affects market outcomes.

Each negotiated contract defines the lump sum amount per enrollee the MCO must pay the hospital system to cover the costs of potential care throughout the year. Following the literature, in the absence of information on the actual timing of negotiations, each contract is assumed to be negotiated annually at the beginning of the fiscal year. In line with this assumption, Cooper et al., 2019 find that most hospital-insurer pairs renegotiate once per year, based on a nationally representative sample of private insurance contracts.

Insurer Payoffs

The following denotes m's increase in net payoff with the network $\mathbf{H}_m$ relative to what could be achieved with $\mathbf{H}_{\mathbf{m}\setminus\{\mathbf{H_s}\}}$ for a contract over all $t \in \mathbf{T}$:

$$V_m(s,\mathbf{T}|\mathbf{H}_m) = WTP_m\big(\mathbf{H_s}|\mathbf{H_m}\big),$$

where $WTP_m\big(\mathbf{H_s}|\mathbf{H_m}\big)$ is given in Equation (6). By proxying for the insurer's change in payoff from adding system s with the aggregate willingness-to-pay for system s hospitals, it is assumed that marginal treatment costs are identical across all hospitals in the market.

Assumption 6B. *Each $h \in \mathbf{H}$ has a constant marginal cost of treatment denoted as θ_{mc}.*

Though this may seem like an implausible assumption, it is implied in how fee-for-service Medicare agrees to reimburse hospitals. Also, many private insurance contracts are negotiated with Medicare rates as a reference point (Cooper et al., 2019). Relaxing this assumption would be complicated by observed cost differences likely being correlated with unobserved variation in patient severity.

Hospital System Payoffs

Denote q_{smt} as the expected (at the time of negotiations) number of enrollees of m who will seek care at a hospital owned by system s in quarter t if is in-network, weighted by resource intensity w_z:[31]

$$q_{smt} = N_{mt}\int_{Z,K,F} w_z\left(\sum_{h\in\mathbf{H_s}} s_{iht}(\mathbf{x_{it}},\mathbf{v_{it}})\right) g_{zkf}(\mathbf{z_{it}},\mathbf{k_{it}},\mathbf{f_{st}})d\mathbf{f_{st}}d\mathbf{k_{it}}d\mathbf{z_{it}}, \tag{8}$$

with $s_{iht}(\mathbf{x_{it}},\mathbf{v_{it}})$ as given in Equation (4). Let R_{sm} denote the lump sum transfer payment system s negotiates with plan m.

Assumption 7B. *If a contractual agreement is reached between any s and m, then s receives some fixed lump sum payment R_{sm} from m.*

[31] Empirically, w_z is the Medicare Severity Weight for a given diagnosis group.

System s's gross payoff from an agreement with m is

$$V_s(m,\mathbf{T}) = R_{sm} - \theta_{mc}\sum_{t\in\mathbf{T}} q_{smt}$$

Aside from expectations being taken over the marginal costs of advertising, the bargaining payoffs for both hospitals and insurers are a particular case of the model in Gowrisankaran et al., 2015 with lump-sum payments, no cost sharing, and constant marginal treatment costs.

Nash Bargaining Problem

The Nash bargaining solution for any pair s and m is the transfer R^*_{sm} that maximizes the weighted product of payoffs from an agreement relative to no agreement, where the bargaining weight $\zeta \in [0,1]$ denotes the share of surplus each party obtains. The lump sum transfer that solves the Nash bargaining problem between s and m is

$$R^*_{sm} = \arg\max_r \left(WTP_m\left(\mathbf{H_s}|\mathbf{H_m}\right) - r\right)^{1-\zeta}\left(r - \theta_{mc}\sum_{t\in\mathbf{T}} q_{smt}\right)^{\zeta}$$

$$= \zeta WTP_m\left(\mathbf{H_s}|\mathbf{H_m}\right) + (1-\zeta)\theta_{mc}\sum_{t\in\mathbf{T}} q_{smt}. \tag{9}$$

Dividing (9) by the expected quantity gives the per-treatment transfer for each s and m

$$P_{sm} = \frac{\zeta WTP_m\left(\mathbf{H_s}|\mathbf{H_m}\right)}{\sum_{t\in\mathbf{T}} q_{smt}} + \tilde{\theta}_{mc}, \tag{10}$$

where the constant is expressed as $\tilde{\theta}_{mc} = (1-\zeta)\theta_{mc}$. The empirical analog of Equation (10) is further discussed in Section 6.2.

5.2.2 Advertising Stage

Each period throughout the negotiated contract, marginal costs of advertising are drawn for each hospital and advertising expenditure is chosen accordingly to maximize profit from negotiations with insurers. Although multi-hospital systems negotiate jointly with insurers, they are assumed to choose advertising expenditure independently each period. Advertising expenditure is set each period as a best response conditional upon the expenditure of all other hospitals as well as the current period's marginal cost of advertising.

Assumption 2A. *For all $h \in \mathbf{H}$ and all $t \in \mathbf{T}$, the marginal cost of advertising mc^{ad}_{ht} is a random variable drawn from a hospital-specific distribution F_h with density f_h.*

After subtracting out expected treatment costs ($\theta_{mc} \sum_{m' \in \mathbf{M}} \sum_{t \in \mathbf{T}} q_{sm't}$), any hospital system s's total profit[32] from offering inpatient services to privately insured patients in period t is

$$\Pi_{st}(\mathbf{a}^*_t) = \left\{ \sum_{m' \in \mathbf{M}} \zeta \Big(WTP_{m'}\big(\mathbf{H_s}|\mathbf{H_{m'}}, \mathbf{a^*_t}\big) - \theta_{mc} q_{sm't}(\mathbf{a}^*_t) \Big) - \sum_{h' \in \mathbf{H_s}} c^{ad}_{h't}(\mathbf{a}^*_t) \right\},$$

where $\mathbf{a}^*_t$ denotes the equilibrium advertising vector in quarter t and $c^{ad}_{ht}(a_{ht})$ is the cost of advertising in t for hospital h associated with advertising expenditure a_{ht}. Any hospital h chooses advertising expenditure a_{ht} by solving[33][34]

$$\begin{aligned}
\frac{\partial \Pi_{st}}{\partial a_{ht}} = {} & \zeta \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \frac{1}{\alpha_i} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \Delta_{iht,c}(\mathbf{v_{iht}}) \ln \left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c)} \right) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}} \\
& - \zeta \theta_{mc} \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \Delta_{iht,c}(\mathbf{v_{iht}}) \Big(\sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c) \Big) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}} \\
& - mc^{ad}_{ht}(a_{ht}),
\end{aligned} \tag{11}$$

[32] Here, "total profit" refers to the expected contributions towards profit from private insurance payers above fixed costs in production and advertising.

[33] Willingness-to-pay per-discharge, which was used in the bargaining model, is multiplied by expected quantity in the firms' profit function, which then becomes the aggregate WTP as given in Equation (6).

[34] WTP and quantity are now explicitly expressed as a function of the advertising vector.

where

$$\Delta_{iht,c}(\mathbf{v_{iht}}) = \frac{\partial(\mathbf{v_{iht}}\tau)}{\partial a_{ht}}\Bigg(\mathbf{I}(h \in c)(1-\phi_{iht}(\mathbf{v_{iht}})) - (1-\mathbf{I}(h \in c))\phi_{iht}(\mathbf{v_{iht}})\Bigg),$$

and derivations are in Appendix B. Note that, unlike in the equations used in the bargaining stage, Equation (11) does not integrate over the marginal costs of advertising. This is because in the bargaining stage, at the time of contract negotiations, all measures are relative to the expected marginal costs of advertising. However, Equation (11) is expressed after the marginal costs are realized and systems choose expenditure accordingly. The marginal effect of willingness-to-pay on profit, ζ, is obtained from the bargaining stage of the model.[35] Every variable in Equation (11) is observed either from data or from estimates in the demand and bargaining stages, except for the marginal cost of advertising, $mc^{ad}_{ht}(a_{ht})$. Therefore, the implied marginal costs can be backed out like in Bertrand Nash pricing games. The procedure used to compute marginal costs is described in Section 6.2.

6 Identification and Estimation

6.1 Identification

Proposition 2 below shows that consideration set probabilities are identified under the following assumptions. First, advertising is excluded from the utility function. Second, conditional upon observed covariates, consideration probabilities are independent across options. Third, the advertising support is large enough such that it contains extreme points where any hospital is necessarily considered with probability approaching one.

Assumption 1I. *For every i and $h \in \mathbf{H} \backslash h_0$ (where h_0 is i's default option), there exists a known covariate $a_{ht} \in \mathbf{v_{iht}}$ and a function of it $f_{ih}(a_{ht})$ such that*
(i) (Exclusion restriction): $\frac{\partial U_{iht}}{\partial f_{ih}(a_{ht})} = 0$
(ii) (Independence across options): $\phi_{ih't}(\mathbf{v}_{ih't})$ *does not depend on* $a_{ht} \forall h \neq h'$.

[35]As to be discussed in Section 8, empirically $\hat{\zeta} = \frac{\zeta}{\alpha}$ where ζ is the hospital's share of surplus to be calibrated.

(iii) (Large support): The closure of the support of a_{ht} conditional on all other covariates contains a point $\overline{a}_{ht}$ such that

$$\lim_{a_{ht}\to\overline{a}_{ht}} A(\mathbf{v_{iht}}) = \infty$$

$$\lim_{a_{ht}\to\overline{a}_{ht}} \frac{A(\mathbf{v_{iht}})}{f_{ih}(a_{ht})} = O(1).$$

Once consideration set probabilities are identified, identification of preference parameters follows from pushing all hospitals' advertising stocks to infinity such that the model converges to a standard discrete choice model. Thus, the identification of utility parameters comes from observed exogenous variation in the propensity of patients with different characteristics (i.e., geographic proximity) to choose a given hospital.

Proposition 2. *If Assumption 1I is satisfied then $pr_{it}(c|\mathbf{v_{it}})$ is identified $\forall i \in \mathbf{I}$ and $\forall c \in \mathbf{C}_i$. Proof: Appendix C*

6.2 Estimation

The demand model is estimated with maximum simulated likelihood. The bargaining model is estimated by calculating the price that solves each Nash-in-Nash bargaining problem. The estimated parameters of the bargaining model are then used as inputs into hospitals' advertising decisions. Marginal costs of advertising are found by inverting advertising first-order conditions. Then, patient welfare and negotiated prices are computed at the advertising levels associated with expected marginal costs. Each of the two stages in the supply model are estimated with separate instrumental variable regressions.

Estimation of the Demand Model

Denote the parameter vector as $\theta = (\beta, \tau)$ where β is the vector of utility parameters and τ is the vector of consideration parameters. The probability of i choosing h as a function of θ is

$$s_{iht}(\mathbf{x_{it}} \mid \theta) = \sum_{c\in\mathbf{C_i}} \prod_{j\in c} \phi_{ijt}(\mathbf{v_{ijt}} \mid \tau) \prod_{j'\notin c} (1-\phi_{ij't}(\mathbf{v_{ij't}} \mid \tau)) s_{iht|c}(\mathbf{x_{it}} \mid \beta), \tag{12}$$

which can be used to construct the likelihood function and estimate θ by maximum likelihood. If (12) were to be estimated directly, choice probabilities would have to be calculated for $2^{\mathbf{H}}+1$ consideration sets for each individual at each guess of θ. Instead, a simulated maximum likelihood approach is used. At each iteration of the maximum likelihood algorithm, R uniform draws are taken for each hospital-individual, with each denoted as ω^r_{ijt}. If $\phi_{ijt}(\mathbf{v_{ijt}}|\tau) > \omega^r_{ijt}$ at the current parameter values, then j is in i's consideration set for that draw. Otherwise, j is not in i's realized consideration set. Thus, the R sets $\{c^r_i \mid r = 1,...,R\}$ for each individual are drawn according to the probabilities

$$pr_{it}(c^r_i|\tau,\mathbf{v_{it}}) = \prod_{j\in c^r_i} \phi_{ijt}(\mathbf{v_{ijt}} \mid \tau) \prod_{j'\notin c^r_i} (1-\phi_{ij'dt}(\mathbf{v_{ij't}} \mid \tau)).$$

Equation (12) is simulated as

$$\hat{s}_{iht}(\mathbf{x_{it}} \mid \theta) = R^{-1}\sum_{r}^{R} s_{iht|c^r_i}(\mathbf{x_{it}} \mid \beta) \rightarrow_p \sum_{c\in\mathbf{C_i}} pr_{it}(c_i|\tau,\mathbf{v_{it}}) s_{iht|c}(\mathbf{x_{it}} \mid \beta),$$

and the log-likelihood function to be maximized is

$$\ln\big(L(\theta)\big) = \sum_{t\in\mathbf{T}}\sum_{i\in\mathbf{I_t}}\sum_{h\in\mathbf{H}} \mathbf{I}(y_{it}=h)\ln\left(\mathrm{R}^{-1}\sum_{r}^{\mathrm{R}} s_{iht|c^r_i}(\mathbf{x_{it}} \mid \beta)\right).$$

Estimation of the Bargaining Stage

Equation (10) gives the linear estimating equation for the bargaining game. The output of the bargaining game, to be used as an input into the advertising game, is the estimated marginal effect of willingness-to-pay on prices, $\hat{\zeta}$. As shown in Equations (6)-(7), to compute WTP one must integrate over the joint density of clinical characteristics, demographic characteristics, and advertising marginal costs. All patients sufficiently ill to visit a hospital are grouped into demographic cells.[36] The within-cell probabilities of each major diagnostic category (MDC) being realized and the average severity weight conditional upon a realized MDC are derived from observed health shocks. Then, each patient's

[36]Patients are grouped by age (0-19, 20-34, 35-45, 46-54, 55-64) and gender.

willingness-to-pay to include a hospital within a given period is the willingness-to-pay conditional upon a health shock, weighted by each diagnosis' probability of occurring and the expected severity. The integration process is only done over clinical characteristics because summing over all patients sufficiently ill to be included in the data effectively integrates over the empirical distribution of the population's locations and demographics. Observations in the top and bottom one percent of WTP per discharge are winsorized.

Marginal costs of advertising are not able to be calculated until the advertising game, and thus they cannot be integrated over during the bargaining game. Endogeneity concerns arise if Equation (10) is estimated by OLS because WTP and expected quantity are measured at the realized advertising levels, rather than the expected levels during contract negotiations. Therefore, Equation (10) is estimated using two-stage least squares. For each $s \in \mathbf{S}$, the log transformation of the number of inpatient beds is used as an instrument. All else constant, larger systems, as proxied by the number of beds, will have higher willingness-to-pay per discharge due to joint bargaining and the internalization of within-system substitution. However, there is no clear reason why the difference between expected and observed advertising expenditure should be dependent upon the size of the hospital system. If system size is uncorrelated with a hospital's marginal cost forecast error, but correlated with WTP per discharge, then system size is a valid instrumental variable. Below, the endogeneity of WTP per discharge will no longer be a concern once $\hat{\zeta}$ is estimated, and marginal costs of advertising can be backed out. Once marginal costs are backed out, WTP and expected quantity for each system are recomputed at the advertising levels corresponding to the fitted marginal costs, and the average fitted prices are then calculated.

Estimation of the Advertising Stage

Each system-quarter's marginal cost of advertising is backed out from the first-order conditions in Equation (11). Hospital-quarters with zero advertising expenditure have not paid any unobserved fixed costs of advertising (Grossman and Shapiro, 1984) and are restricted to have zero expenditure in counterfactuals.[37] If $mc_{ht}^{ad} > 0$ then it can be

[37] 88.28% of hospital-quarters have positive advertising. Two hospitals do not advertise in any quarter.

expressed as

$$mc_{ht}^{ad} = \hat{\zeta} \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \frac{1}{\alpha} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \Delta_{iht,c}(\mathbf{v_{iht}}) \ln\left(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c)}\right) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$-\zeta \theta_{mc} \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \Delta_{iht,c}(\mathbf{v_{iht}}) \Big(\sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c) \Big) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}}, \qquad (13)$$

where the integration is implemented as just described in the bargaining stage. Computing (13) requires estimates for θ_{mc} and ζ. Recall that in the bargaining stage regressions, the theoretical equivalent of the estimated coefficient on WTP per discharge is $\hat{\zeta} = \frac{\zeta}{\alpha}$, where ζ is the Nash bargaining weight and α is the constant marginal utility of income. The theoretical equivalent of the constant term in the bargaining regressions is $\tilde{\theta}_{mc} = (1-\zeta)\theta_{mc}$. The model does not allow for distinguishing between ζ and α from the estimated bargaining coefficients. Therefore, to back out estimates for θ_{mc}, ζ is calibrated based on estimates found in the related literature,[38] and $\zeta = .5$ is used in baseline results. This implies $\theta_{mc} = 2\tilde{\theta}$, where $\tilde{\theta}$ is previously estimated in the bargaining stage. Then, as seen in (13) above, θ_{mc} is to be multiplied by the calibrated $\zeta = .5$ such that empirically, the coefficient on the second term is equivalent to the constant from the bargaining estimating equation. Equation (13) expresses the realized marginal costs, rather than the expected marginal costs at the time of negotiations. To approximate expected marginal costs, the following linear-log specification is used:[39]

$$mc_{ht}^{ad}(a_{ht}) = \alpha_h^{mc} + \alpha^{mc} \ln(a_{ht}) + \varepsilon_{ht}^{ad},$$

where α_h^{mc} are alternative-specific constants. Estimating the marginal cost function requires controlling for the endogeneity of advertising. There is likely to be correlation

[38] Gowrisankaran et al., 2015 begin their analysis by using a specification with $\zeta = .5$, then show that for 3/4 of MCOs, hospitals obtain less than half of the share of surplus. Ho and Lee, 2017 estimate ζ to be between .31-4. In simulations, Balan and Brand, 2023 run specifications with $\zeta = .4, .5, .6$.

[39] Advertising expenditure is log transformed here to ensure that its fitted value is non-negative.

between observed advertising expenditure and unobserved marginal cost shocks. For a proposed instrument to be valid, then conditional on hospital-specific constants, it needs to be uncorrelated with the unobserved hospital-quarter marginal cost shock and correlated with observed hospital-quarter advertising. The panel structure of the data is utilized to make an assumption in the spirit of Hausman, 1996 and Nevo, 2001. The identifying assumption is that controlling for observed hospital-quarter advertising, hospital-quarter marginal cost shocks are independent across quarters. Given this assumption, any hospital-quarter's marginal cost shock will be independent of the hospital's advertising expenditure in other quarters. Therefore, if hospital-specific quarterly demand shocks are correlated over time,[40] advertising expenditure will be correlated across quarters and can be used as a valid instrumental variable. Each hospital's logged transformation of one month lagged advertising expenditure is used as an instrument.

After calculating WTP per discharge using previously described methods and obtaining an estimate $\hat{\zeta}$ for the marginal effect of WTP per discharge on prices, WTP per discharge is recomputed at fitted marginal costs. The prices negotiated by firms and the consumer welfare associated with these fitted marginal costs can then be compared to the equivalent measures in a counterfactual equilibrium.[41] That is, a hospital's fitted advertising expenditure to be used to compute fitted prices and compare counterfactual outcomes is

$$\hat{a}_{ht} = exp\left(\frac{\hat{mc}_{ht}^{ad} - \hat{\alpha}_h^{mc}}{\hat{\alpha}^{mc}}\right).$$

For each period post-merger,[42] changes in the WTP per discharge for each system are initially calculated at pre-merger fitted advertising levels. The objective is to find the new advertising expenditure for each $h = 1, 2, ...n$ with pre-merger positive advertising such

[40] First-stage results providing evidence of these instruments' relevance are in Appendix I.

[41] Due to already integrating over consideration sets and clinical characteristics, the average marginal cost is used.

[42] Currently, the merger is only simulated for one quarter and the quarter-specific percentage changes in WTP per person are used to predict annual price changes.

that

$$\mathbf{f_t}(\mathbf{a}_t) = \begin{bmatrix} \frac{\partial \Pi_{s_1 t}(a_{1t},\ldots,a_{nt})}{\partial a_{1t}} \\ \frac{\partial \Pi_{s_2 t}(a_{1t},\ldots,a_{nt})}{\partial a_{2t}} \\ \vdots \\ \frac{\partial \Pi_{s_n t}(a_{1t},\ldots,a_{nt})}{\partial a_{nt}} \end{bmatrix} = 0.$$

Given the initial guess $\mathbf{a}_t$ for the vector of advertising levels, an improved guess is iteratively found until the difference between successive guesses of the advertising vector is sufficiently close to zero. Anderson acceleration is used to solve for these new equilibrium advertising levels. Anderson acceleration (Anderson, 1965) is a method to accelerate fixed point convergence for computationally intensive problems. Conlon and Gortmaker, 2020 provide evidence that variations of this algorithm have better convergence properties compared to Newton and quasi-Newton methods in the context of BLP contraction mappings. Next, all systems' new WTPs per discharge are calculated at the simulated post-merger advertising stocks. Finally, the corresponding negotiated price changes can be obtained from the previously estimated marginal effect of WTP per discharge on negotiated prices found in the bargaining game.

7 Estimation Results

Demand

Table 6 below displays the estimated coefficients and standard errors. The results from a full consideration model are displayed in Appendix I. The model incorporates spatial distance, advertising, intrinsic hospital characteristics[43], and patient demographics and clinical characteristics to capture patient preferences across different hospitals. Distance is measured in miles and divided by 10. Severity is measured according to the Medicare Severity Weight of each patient's Diagnosis Related Group, and is divided by 100. Median Income is in 10,000s of dollars. A random sample of 10,000 patients is used and 200

[43] The full hospital names corresponding to each hospital ID number in Table 6 are listed in Appendix L.

consideration sets are drawn for each patient at each iteration of the maximum likelihood algorithm. The utility for the outside option is normalized to 0. The distance to the outside option used in the attention function is specified for each patient as equal to the distance from the farthest away feasible inside option.

In the utility stage, hospital fixed effects are included as a measure of vertical product differentiation and a distance function is included as a measure of horizontal product differentiation. Interaction terms in utility capture that the marginal disutility of distance varies with income and severity. The attention function consists of a distance function, advertising function, and a constant.[44] Similar to in utility, the marginal effects of both distance and advertising on attention vary with patient income and severity. I also include interaction between distance and advertising, following its positive effect in the reduced-form results from Section 4.

As expected, distance has a negative coefficient in both utility and consideration. The coefficient on the distance variable in utility suggests a substantial negative relationship between distance and preferences. This result indicates that patients place significant value on proximity, with closer hospitals being considerably more attractive. As distance increases, the likelihood of a patient choosing a particular hospital diminishes sharply, conditional upon consideration. Additionally, attention is also decreasing in distance. Taken together, this reflects a cost of traveling as well as less attention towards farther away hospitals.

Patients experiencing more severe health conditions are less willing and less able to travel for care, as their utility from, and attention to, distant options diminish more sharply compared to those with milder conditions. This reflects the increased urgency of their conditions and is suggestive of time constraints playing a role in both preferences and attention. Higher-income patients are more willing-to-travel, possibly due to lower travel costs associated with greater ease of transportation (i.e., owning a car). Previous survey results corroborate this finding of lower-income patients having more barriers to traveling to obtain medical care (Syed et al., 2013). On the contrary, lower-income patients are more

[44] Problems associated with multicollinearity arise when including alternative-specific constants in the attention function along with the advertising function. Including both of these in the attention function could be attainable with a longer panel consisting of more within-hospital variation in observed advertising expenditure over time.

likely to be aware of farther away options.

The model also includes alternative-specific constants in utility for each hospital, capturing unobserved hospital-specific attributes that affect patients' utility. These constants reflect vertical differentiation, representing time-invariant unobserved hospital characteristics such as reputation or perceived quality of care that distinguish each hospital beyond its location. The variation in these coefficients indicates significant differences in patient preferences for specific hospitals. For instance, Hospital 5 (Children's Hospital of Philadelphia) shows a particularly high positive effect, suggesting that patients perceive it as offering superior services. Conversely, Hospital 3 (Methodist Hospital) displays a strong negative effect, indicating that patients derive less utility from choosing this hospital compared to others, potentially due to perceptions of lower service quality.

These results suggest that while proximity is a key driver of hospital choice, hospitals are differentiated on quality attributes that make them appealing to patients even when they are farther away. However, a patient in my model will never choose a non-considered hospital, even if it could offer them exceptional quality. My model contrasts with the existing literature by modeling distance as affecting choices for both preference and attention-related reasons. Although attention is decreasing in distance, hospitals can successfully increase patients' attention towards them by investing in advertising.

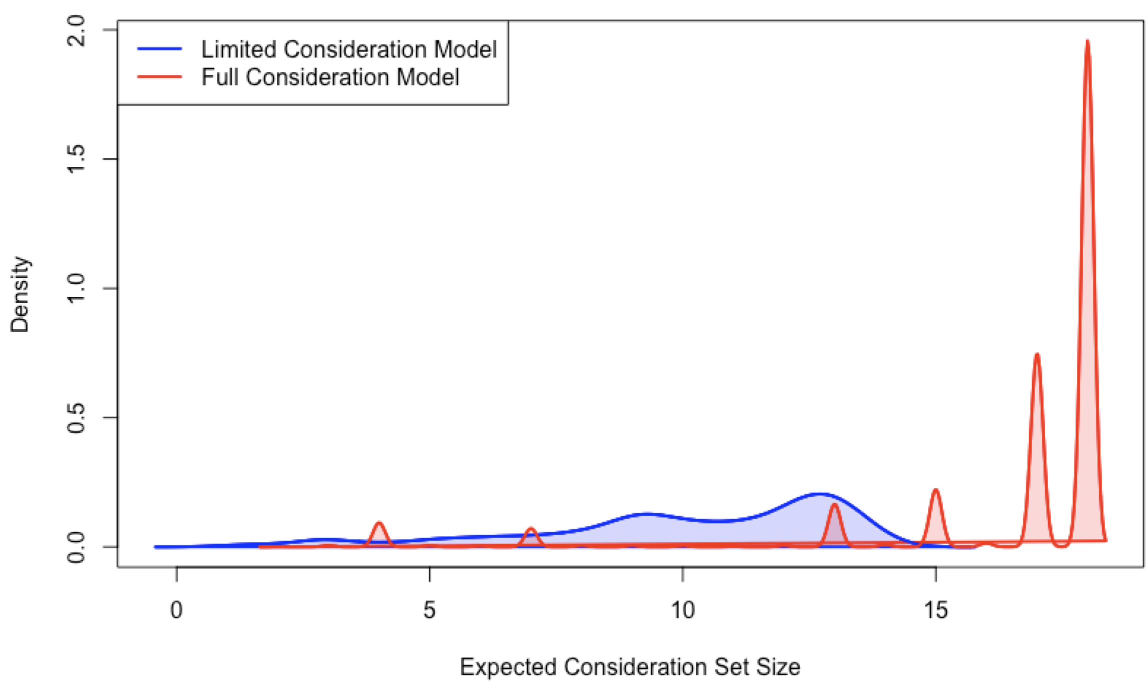
Advertising stock has a positive marginal effect on attention, the magnitude of which is increasing in geographic distance. This result is expected following the reduced-form evidence in Section 4. This positive interaction suggests that advertising can help mitigate the disadvantage of being located farther from potential patients. For hospitals with a strong advertising presence, the negative impact of distance is less pronounced, indicating that strategic marketing can enhance their competitive positioning even when they are not the nearest and/or highest quality option for many patients. As mentioned in the introduction, hospital prices vary widely across competing hospitals even for plausibly undifferentiated services. This phenomenon is difficult to rationalize as a result of existing hospital demand models embedded in models of hospital-insurer bargaining. In the coming sections, I explore the role of inattention on the distribution of negotiated prices.

Table 6: Demand Results

Variable	Coefficient	Standard Error
Utility Variables		
Distance	-3.1221	1.0239
Distance * Severity	-0.1024	0.9762
Distance * Income	0.1844	1.0012
I(Hospital 1)	0.0556	0.9621
I(Hospital 2)	0.3031	0.8480
I(Hospital 3)	-1.7387	0.9488
I(Hospital 4)	1.2679	0.9973
I(Hospital 5)	2.6212	1.0006
I(Hospital 6)	-0.0163	1.2287
I(Hospital 7)	-1.5028	1.0183
I(Hospital 8)	0.0280	0.9760
I(Hospital 9)	0.2516	0.9349
I(Hospital 10)	-0.6700	1.0412
I(Hospital 11)	-0.3691	1.0116
I(Hospital 12)	1.2178	0.9597
I(Hospital 13)	0.6904	1.1346
I(Hospital 14)	0.8306	0.9819
I(Hospital 15)	-0.9677	0.9537
I(Hospital 16)	0.0806	0.9746
Consideration Variables		
Ad Stock	0.6148	1.0022
Ad Stock * Distance	0.2480	0.9901
Distance	-1.1757	0.9975
Distance * Severity	-1.2409	1.2050
Distance * Income	-0.2444	0.8854
Intercept	-0.1619	1.0060

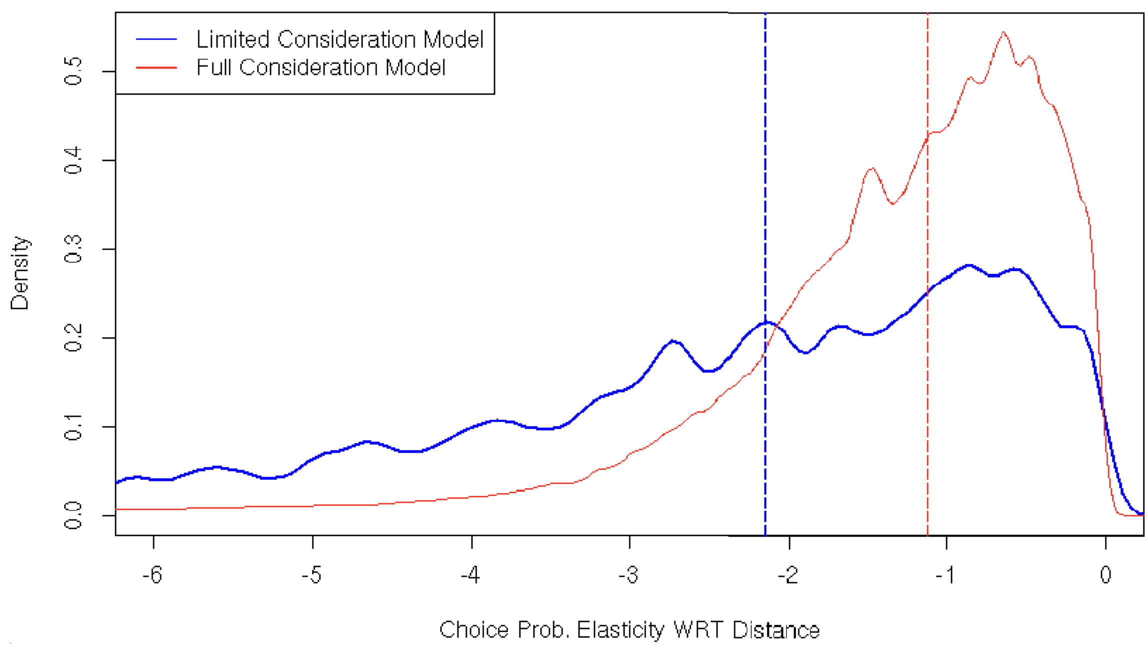
Figure 3 below illustrates how limited consideration decreases the sizes of individuals' sets of hospitals to be chosen from. Due to the independence of consideration shocks across options (Assumption 1D), the expected cardinality of a patient's consideration set is the sum of each inside-hospital's consideration probability. The plot in red shows the density of the choice set size patients would have if they were fully aware of all options. The blue plot is the corresponding density with the limited consideration model. In theory, the two plots could be identical. If the true state of the world consisted of all patients considering every option, then, in principle, the maximum simulated likelihood algorithm's estimates should reflect this. The divergence between these densities highlights how patients choosing from a limited set of hospitals may impact substitution patterns and, in turn, affect equilibrium prices.

Figure 3: Expected Cardinalities of Consideration Sets



The results displayed in Figure 3 reveal that it is unlikely for any patient to be attentive to all feasible options upon seeking hospital care. Demand results from Table 6 point to the limited sets of hospitals being considered by patients as being heavily influenced by geographic proximity. Since distant hospitals are less likely to enter consideration sets, patients disproportionately select closer hospitals compared to if they were fully attentive. Hypothetically moving a hospital marginally closer to a patient is irrelevant if the patient is inattentive towards the hospital both before and after the change. A full consideration model cannot detect this relationship, leading to a biased choice elasticity with respect to distance. As a result, the limited consideration model captures a steeper decline in the likelihood of choosing a hospital as the distance increases—leading to higher distance elasticities. Figure 4 below plots the choice elasticities with respect to distance in each model for each hospital-patient pair. Results imply that the median hospital-patient pair has a distance elasticity that is nearly twice that of the respective measure in the full consideration model. The formula used for distance elasticities is derived in Appendix M.

Figure 4: Distance Elasticities



Bargaining

To convert WTP estimates into dollar values, I regress the actual revenues per weighted discharge from inpatient services of privately insured patients onto the estimated WTP per discharge. This conversion enables the interpretation of the utility derived from patient choices in monetary terms, which is crucial for analyzing the outcomes of negotiations between hospitals and insurers. Since the demand model is estimated under the assumption that patients do not observe price variation across in-network hospital options at the time of seeking care, price does not directly enter their utility function. As a result, this conversion is not possible from choice estimates alone. Table 7 presents OLS and 2SLS results from the estimating equation in the bargaining stage of the model.

The 2SLS approach is preferred, as discussed in Section 6, due to concerns about the potential endogeneity of WTP. Specifically, within the model framework, WTP per discharge is computed at this stage without properly controlling for the endogeneity of advertising. To address this, the 2SLS approach helps isolates exogenous variation in WTP. The results from the first-stage regressions, included in Appendix G, verify the relevance of the instruments used. Next, the coefficients from this model are used as inputs into the advertising game to back out marginal costs.

Table 7: Bargaining Results

	(OLS)	(2SLS)
Intercept	6.8924***	6.3928**
	(1.4013)	(2.4161)
WTP per weighted discharge	5.7280***	6.3251*
	(1.5953)	(2.8421)
Observations	102	102
R^2	0.114	

Marginal Costs of Advertising

Previous research has suggested that as firms increase advertising expenditures, the likelihood that a consumer will encounter a given ad more than once rises, making it increasingly likely that each subsequent dollar spent on advertising reaches a consumer who has already seen the ad. This concept is rooted in the work of Grossman and Shapiro, 1984, who emphasize that informative advertising can become less effective as expenditure increases, leading to the expectation of rising marginal costs with increased advertising due to diminishing returns in reaching new consumers.

However, my results, presented in Table 8, indicate a contrasting pattern: the marginal costs of advertising appear to decrease as expenditure increases. This suggests the presence of scale economies in advertising, where larger campaigns may benefit from lower costs per additional exposure. These scale economies could be attributed to factors such as volume discounts in media purchases or more efficient allocation of resources in larger campaigns. The findings challenge the conventional perspective and imply that, within this market context, firms might achieve greater reach at a lower marginal cost as they scale their advertising efforts.

The first-stage results, shown in Appendix H, support the validity of the instruments used in the second-stage regression. These instruments ensure that the estimated relationship between advertising expenditures and marginal costs properly accounts for potential endogeneity. This addresses the possibility that unobserved factors influencing advertising choices, such as the strategic responses by competitors, might otherwise bias the estimates.

Table 8: Marginal Cost Results, Second Stage

	(OLS)	(2SLS)
Intercept	929.6824***	719.8842***
	(101.5520)	(128.9755)
$\ln(a_{ht})$	-180.0707***	-123.8374***
	(23.1844)	(31.0929)
Observations	50	50
R^2	0.557	

8 Counterfactual of Full Consideration

Compensating Variation

In the model, patients are necessarily weakly worse off under limited consideration than in a counterfactual world where they are costlessly attentive to all options.[45] I convert utils to dollars using supply-side estimates to assess the magnitude of each patient's welfare change in the event where they are fully attentive.

Recall that, consistent with the literature on hospital-insurer bargaining, I have assumed that summing over all patients sufficiently ill to be included in the data effectively integrates over the empirical distribution of the population's locations and demographics. This approach enables the calculation of the ex-ante WTP[46] based on observed data, which only includes patients who have experienced a health shock requiring inpatient care. Therefore, when calculating the aggregate ex-ante WTP for each insurer-system pair, I integrate only over the probabilities of different diagnoses, given that a health shock has occurred.

This subsection shifts focus to computing the ex-ante WTP for each observed patient in the data. This method allows for inferences about the monetary losses patients experience due to inattention. Two measures with different interpretations are computed below. First, I calculate each patient's compensating variation, conditional upon a health shock. This compensating variation represents the amount of money a patient would need to receive at the beginning of the year, such that in the event of any health shock requiring inpatient care, they would be indifferent between making choices with limited consideration and receiving the compensation or having the ability to make choices with full consideration.

Second, I calculate each patient's unconditional compensating variation using auxiliary claims data from a large private health insurer.[47] I observe the insurer's roster of enrollees, each enrollee's age and gender, and histories of inpatient admissions for each quarter. I use this nationally representative sample to approximate the probability of a patient in each

[45]Note that this is not necessarily the case if a micro-foundation where attention is costly was used (Caplin et al., 2019).

[46]This is the terminology used by Capps et al., 2003 to describe the WTP at the beginning of the contract before any health shocks are realized.

[47]This auxiliary data is from the Optum Clinformatics Data Mart.

demographic cell having a health shock requiring inpatient care each quarter. Then, from the conditional compensating variations computed as described in the previous paragraph, I multiply by the probability of having an inpatient admission each quarter, then multiply by 4 to get an annual measure. This second compensating variation gives an estimate of the amount each observed patient would have been willing to pay at the beginning of the year, before any health shocks or cost shocks are realized. Summary statistics for this auxiliary dataset are in Appendix N.

For any i that has a health shock requiring care, consumer surplus before the realization of c is given by

$$\mathbb{E}(CS_i) = \int_{Z,F} \frac{1}{\alpha_i} \sum_{c \in \mathbf{C_i}} pr_{it}\big(c|\mathbf{v_{it}}\big)\mathbb{E}(CS_i|c, \mathbf{x_{it}})g_f(\mathbf{f_{st}})g_z(\mathbf{z_{it}}|\mathbf{k_{it}})d\mathbf{f_{st}}d\mathbf{z_{it}} + d$$

$$= \int_{Z,F} \frac{1}{\alpha_i} \sum_{c \in \mathbf{C_i}} pr_{it}\big(c|\mathbf{v_{it}}\big)\ln\big(\sum_{j \in c} exp(\mathbf{x_{it}}\beta)\big)g_f(\mathbf{f_{st}})g(\mathbf{z_{it}}|\mathbf{k_{it}})d\mathbf{z}_{it} + d,$$

where the last line follows from the distributional assumption on ε_{ih}, and d is an unknown constant. The change in consumer surplus that results from an information intervention making patients costlessly attentive to all options is obtained by estimating $\mathbb{E}(CS_i)$ both before and after patients have full consideration and then taking the difference:

$$\Delta\mathbb{E}(CS_i) = \int_{Z,F} \frac{1}{\alpha} \sum_{c \in \mathbf{C_i}} pr\big(c|\mathbf{v_{it}}\big)\big[\ln\big(\sum_{j' \in \mathbf{H}} exp(\mathbf{x_{ij't}}\beta)\big) - \ln\big(\sum_{j \in c} exp(\mathbf{x_{ijt}}\beta)\big)g_f(\mathbf{f_{st}})g_z(\mathbf{z_{it}}|\mathbf{k_{it}})d\mathbf{f_{st}}d\mathbf{z_{it}}. \tag{14}$$

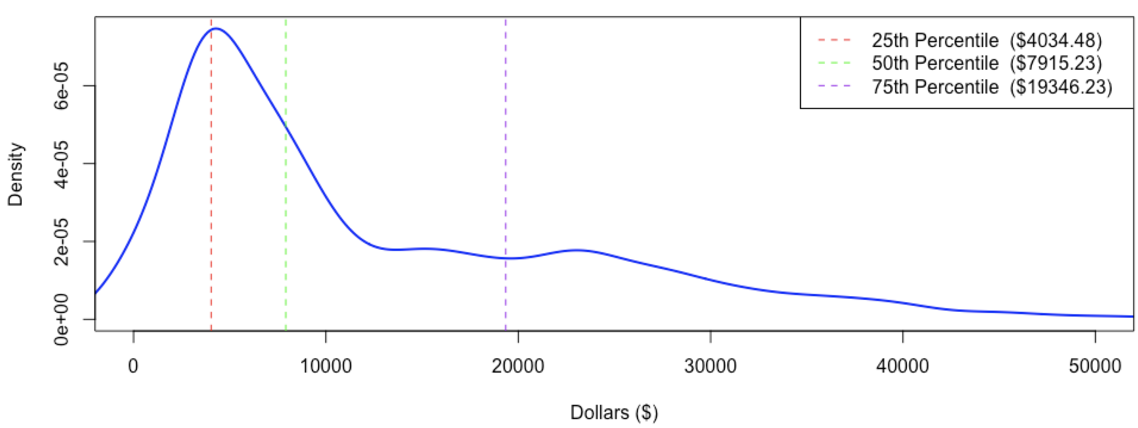
Computing (14) requires knowing the marginal utility of income α, which cannot be observed from demand estimates alone because consumers are price insensitive (Assumption 3B). As discussed in Section 6.2, ζ is calibrated to 0.5, resulting in $\alpha = \frac{.5}{6.3251}$, where 6.3251 is the estimated coefficient from Table 7. Next, each patient's conditional compensating variation is computed and $\Delta\mathbb{E}(CS_i)$ is multiplied by 1,000 to get the change in utility in terms of dollars.[48]

[48]This is consistent with advertising expenditure and hospital revenue being estimated in terms of thou-

The densities of patients' compensating variations are plotted in Figures 5 and 6 below. Focusing first on the conditional measures in Figure 5, the median compensating variation is computed to be \$7,915.23. The long right tail indicates that some patients are much more heavily harmed. Figure 6 plots the unconditional annual compensating variations. The median patient would have to be compensated \$376.56 dollars at the beginning of the year to be equally as well off as if they had full consideration. To put these amounts in perspective, in 2018 the average annual premium for employee-sponsored health insurance was \$6,896 for single coverage and \$19,616 for family coverage (Claxton et al., 2018). Unconditional compensating variations suggest that the median enrollee with single coverage would require a 5.45% decrease in annual premiums, and the median family of four would require a 7.66% decrease to be as well off as if they were fully attentive.

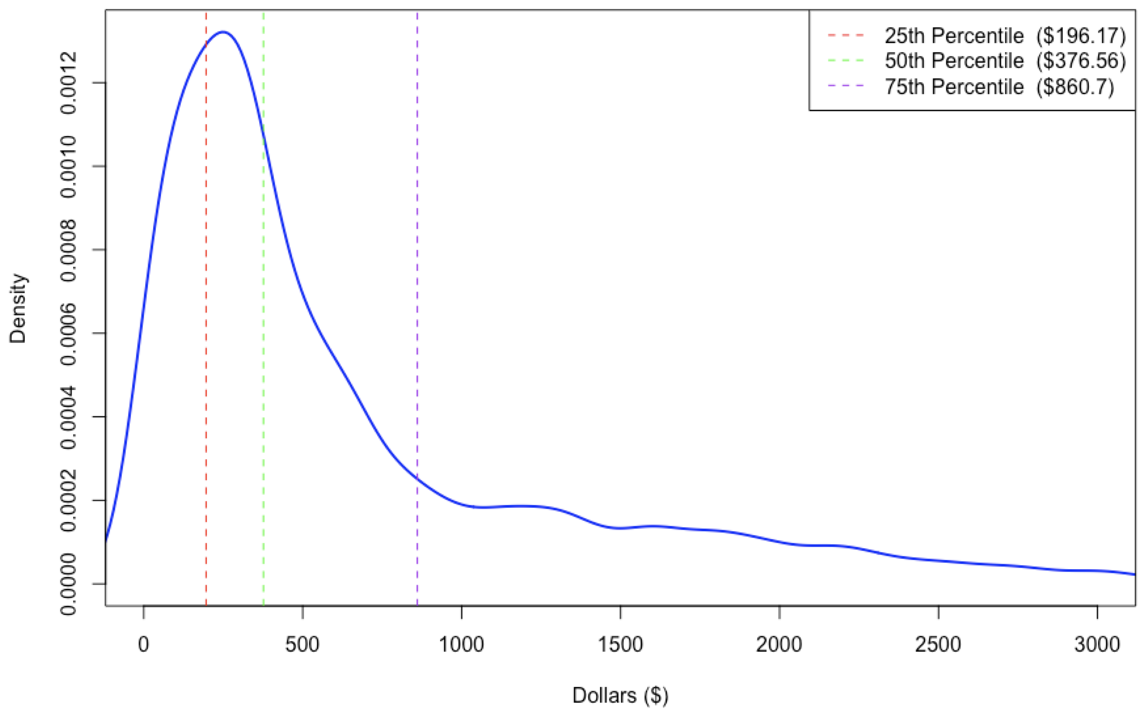
This confirms the proposition in Saurman, 2016 that, conditional upon traditional measures such as travel distance and insurance coverage, a lack of awareness of all available health care options reduces the realized fit between patients and hospitals by economically significant margins. The optimal policy responses to correct for these consumer surplus losses are dependent upon the underlying mechanisms driving consideration set formation. The possibility of combining a micro-foundation for consideration set formation with a model of price formation is left to future work.

Figure 5: Compensating Variation from Limited Consideration, Conditional on a Health Shock Requiring Inpatient Care



sands of dollars.

Figure 6: Annual Unconditional Compensating Variation from Limited Consideration



Price Changes

This section analyzes how inattention affects hospital prices. Figure 7 shows a scatter plot of each hospital system's average price per discharge against the predicted percentage change in prices under a full consideration counterfactual. Figure 8 shows a similar plot at the system-plan level. When patients are assumed to be fully attentive to all in-network options, insurers gain more bargaining leverage, resulting in a median price decrease of 8.86% across system-insurer pairs.

This suggests that having well-informed patients can lead to meaningful price reductions in negotiated rates for hospital services. Hospitals with higher initial prices experience larger reductions when consideration sets are expanded, indicating that some of their pricing power stems from patients' limited attentiveness towards all alternatives. Figure 9 further illustrates these effects through histograms of hospital-insurer negotiated prices under limited and full consideration models. The distribution shifts leftward under the full consideration scenario, showing that broader patient consideration leads to lower and less dispersed prices.

Figure 7: System Price Changes in a Counterfactual of Full Consideration In Relation To Current Prices

Figure 8: System-Plan Price Changes in a Counterfactual of Full Consideration In Relation To Current Prices

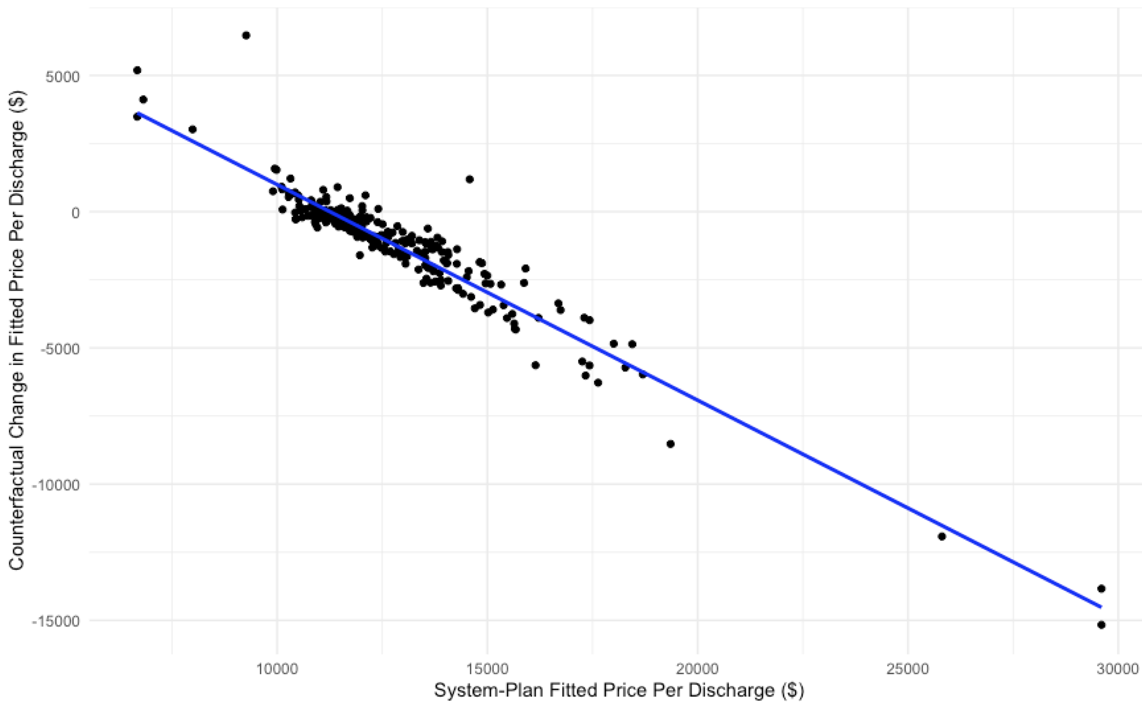
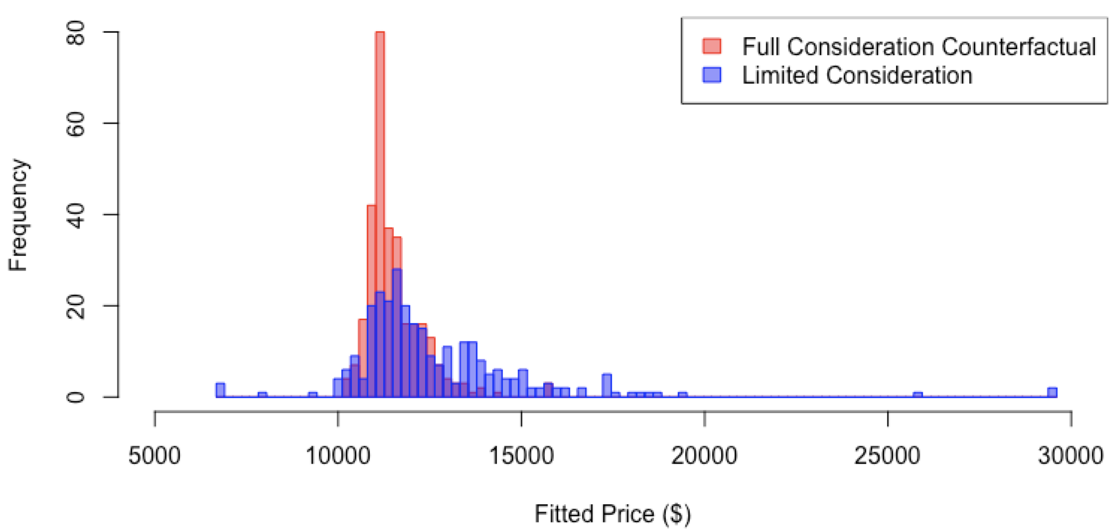


Figure 9: Histograms of System-Plan Prices



The broader implications of these findings suggest that increased patient attentiveness could significantly reduce national healthcare spending. An average system-plan price reduction of 8.86% applied to the $408.07 billion in private insurance spending on inpatient care in 2018 (CMS, 2024a) would result in savings of about $36.15 billion annually, assuming that insurance network structures remain unchanged. These results emphasize the role of patient behavior in shaping price outcomes and how limited consideration can lead to artificially higher prices. However, the distribution of these price changes across hospitals is uneven, and providing patients with more information can help the financial stability of hospitals with initially lower negotiated prices.

Although outside the scope of my model, recent results imply that when there are increases in the prices insurers pay hospitals, the insurers pass on these higher costs approximately one-for-one onto consumers in the form of higher premiums (Brot-Goldberg et al., 2024). Given the average employee-sponsored insurance premiums described in the previous subsection, my results imply that the median family's employee-sponsored health insurance premium would be about $1,738 lower if patients were fully attentive when seeking care. As a result of the close connections between insurance and labor markets resulting from the prevalence of employee-sponsored insurance, the aggregate price increases driven by limited consideration have further implications for local economic outcomes, such as lower wages. Brot-Goldberg et al., 2024 find that an exogenous 1% increase in healthcare prices leads to a 0.27% decrease in county-level income per-capita. Applied to my results, this implies that income per-capita in Philadelphia County would be about 2.39% higher with fully attentive patients.

These price changes reflect shifts in bargaining leverage, which amplify the overall economic impact of limited consideration beyond what is captured through compensating variations alone. Given that limited consideration drives market power as manifested by the ability to negotiate higher prices, a key question arises: how does accounting for limited consideration influence predicted price changes in counterfactual market scenarios? The next section explores this question in detail.

9 Merger Simulation

The model is applied to simulate the price changes resulting from a merger between two hospital systems. As discussed in the introduction, a realized contested merger between two Philadelphia-area hospital systems is used as a natural experiment to compare model predictions. Before describing the merging firms and environment in more depth, equations for the price effects of a merger with limited consideration are derived. Consider two systems s and s' that propose to merge, where $\mathbf{H_s}$ and $\mathbf{H_{s'}}$ denote the sets of hospitals owned by s and s', respectively. Within the model, the predicted price effect of a merger between s and s' is equal to the post-merger WTP per discharge for the merged firm minus the weighted sum of pre-merger WTP per discharge for the two firms, with weights being proportional to the relative pre-merger quantities:

$$\Delta P_{s,s'} =$$

$$\zeta \sum_{t\in\mathbf{T}} \sum_{m\in\mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \sum_{c\in\mathbf{C_i}} \left[\frac{pr_{it}(c|\mathbf{v_{it}^{Post}}) WTP_{it|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}^{Post}})} - W_{smt} \frac{pr_{it}(c|\mathbf{v_{it}}) WTP_{it|c}(s|\mathbf{x_{it}})}{q_{smt}(\mathbf{x_{it}},\mathbf{v_{it}})} - (1-W_{smt}) \frac{pr_{it}(c|\mathbf{v_{it}}) WTP_{it|c}(s'|\mathbf{x_{it}})}{q_{s'mt}(\mathbf{x_{it}},\mathbf{v_{it}})} \right] g_{zkf}(\mathbf{z_{it}},\mathbf{k_{it}},\mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$= \zeta \sum_{t\in\mathbf{T}} \sum_{m\in\mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \sum_{c\in\mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \left[\frac{WTP_{it|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}^{Post}})} - W_{smt} \frac{WTP_{it|c}(s|\mathbf{x_{it}})}{q_{smt}(\mathbf{x_{it}},\mathbf{v_{it}})} - (1-W_{smt}) \frac{WTP_{it|c}(s'|\mathbf{x_{it}})}{q_{s'mt}(\mathbf{x_{it}},\mathbf{v_{it}})} \right] g_{zkf}(\mathbf{z_{it}},\mathbf{k_{it}},\mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$+ \zeta \sum_{t\in\mathbf{T}} \sum_{m\in\mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \sum_{c\in\mathbf{C_i}} \delta_{c,it} \frac{WTP_{it|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}^{Post}})} g_{zkf}(\mathbf{z_{it}},\mathbf{k_{it}},\mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}, \tag{15}$$

where

$$\delta_{c,it} = pr_{it}(c|\mathbf{v_{it}^{Post}}) - pr_{it}(c|\mathbf{v_{it}}),$$

such that $\sum_{c\in\mathbf{C_{it}}} \delta_{c,it} = 0$. $q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}^{Post}})$ and $q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}})$ are the case-mix adjusted expected quantities at pre- and post-merger advertising stocks, and

$$W_{smt} = \frac{q_{smt}(\mathbf{x_{it}},\mathbf{v_{it}})}{q_{smt}(\mathbf{x_{it}},\mathbf{v_{it}}) + q_{s'mt}(\mathbf{x_{it}},\mathbf{v_{it}})}$$

is the relative pre-merger weighted quantity of s. Adding and subtracting $\sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \frac{WTP_{it|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}},\mathbf{v_{it}})}$ to the first term in (15) results in

$$\Delta P_{s,s'} = \zeta \underbrace{\sum_{t \in \mathbf{T}} \sum_{m \in \mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \left[\frac{1}{q_{s+s',mt}(\mathbf{x_{it}}, \mathbf{v_{it}^{Post}})} - \frac{1}{q_{s+s',mt}(\mathbf{x_{it}}, \mathbf{v_{it}})} \right] \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) WTP_{it|c}(s+s'|\mathbf{x_{it}}) g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}}_{\text{Quantity Effect}}$$

$$+ \quad \underbrace{\Delta P^{pre}_{s,s'}}_{\text{Diversion Effect}}$$

$$+\zeta \underbrace{\sum_{t \in \mathbf{T}} \sum_{m \in \mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \sum_{c \in \mathbf{C_i}} \delta_{c,it} \frac{WTP_{it|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}}, \mathbf{v_{it}^{Post}})} g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}},}_{\text{Consideration Effect}} \tag{16}$$

where $\Delta P^{pre}_{s,s'}$ is the total price effect evaluated at the pre-merger distribution of consideration sets:

$$\Delta P^{pre}_{s,s'} = \zeta \sum_{t \in \mathbf{T}} \sum_{m \in \mathbf{M}} \frac{N_{mt}}{\alpha} \int_{Z,K,F} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \frac{WTP_{i|c}(s+s'|\mathbf{x_{it}})}{q_{s+s',mt}(\mathbf{x_{it}}, \mathbf{v_{it}})} - W_{smt} \frac{WTP_{it|c}(s|\mathbf{x_{it}})}{q_{smt}(\mathbf{x_{it}}, \mathbf{v_{it}})} - (1-W_{smt}) \frac{WTP_{it|c}(s'|\mathbf{x_{it}})}{q_{s'mt}(\mathbf{x_{it}}, \mathbf{v_{it}})} g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}.$$

Equation (16) expresses the price effect as a separable function of three terms. The first term is the quantity effect of the merger. This term holds consideration probabilities constant when calculating WTP per discharge, and multiplies the pre-merger joint WTP for s and s' by the difference in inverse expected quantity post and pre-merger. This term will be negative if the expected quantity increases post-merger. If the hospitals in s and s' are not weak substitutes (i.e., are far apart geographically), then the expected quantity may increase post-merger while the joint WTP does not. The quantity effect estimates the extent to which case-mix adjusted quantity increases post-merger, while treating merging products as if they all have diversion ratios of zero.

The second term, the diversion effect, is most similar to existing models of mergers in negotiated price markets. Existing models only allow for a full consideration equivalent of the diversion effect, and do not account for merger-induced changes to the other terms in (16). For any s and s', the term $\Delta P^{pre}_{s,s'} \geq 0$ and is increasing in the substitutability of the two merging firms' locations. This term does not account for any merger-induced changes in the sets of hospitals that patients consider nor any changes in the newly merged system's expected quantities.

The third term in (16), the consideration effect, accounts for post-merger repositioning of consideration probabilities. It is the weighted sum of post-merger WTP per discharge within each consideration set. Each consideration set's weight is the change in probability of that set being realized post-merger. Decomposing the total price effect in this way provides better insight into the drivers of price changes. This may benefit antitrust authorities in regard to determining potential conditions firms must meet for a merger to be approved. For example, if changes in post-merger consideration probabilities are the primary reason a merger is deemed anti-competitive, regulators may allow the merger on the condition that the firms continue separate marketing.

Using a Retrospective Merger as a Natural Experiment

Jefferson Health is a non-profit system operating 13 general acute care hospitals in Pennsylvania and New Jersey. This analysis includes only the five hospitals located in Pennsylvania in or immediately outside of Philadelphia County. Three of the locations, including the flagship Thomas Jefferson University Hospital, are included in the sample. Two relevant locations, Abington Hospital and Abington-Lansdale Hospital, are not in the data due to being located in neighboring Montgomery County. In the price difference-in-differences regressions below, only the Philadelphia-area locations owned by Jefferson are classified as treated post-merger. In the merger simulation, data limitations in the structural model restrict focus to the three Philadelphia County locations. As shown previously in Table 2, these three locations have a collective in-sample market share of 23%.

Einstein Healthcare Network is a non-profit system with three general acute care hospitals in the Philadelphia area. The system's flagship location, Einstein Medical Center Philadelphia, is included in the structural model and, at the time of the merger, accounted for approximately 70% of the system's inpatient revenue (FTC v. Thomas Jefferson University, 2020). The other two locations, Einstein Medical Center Elkins Park and Einstein Medical Center Montgomery, are located in neighboring Montgomery County. Similar to with Jefferson, Einstein's Montgomery County locations are excluded from the structural model's sample, but are included in the price difference-in-differences regressions.

In September 2018, Jefferson and Einstein agreed to merge. In February 2020, with the merger proceedings not yet finalized, the FTC motioned to block the merger out of concern that it would be anti-competitive. In December 2020, a federal district court judge rejected the government's claim that the merger would be anti-competitive under Section 7 of the Clayton Act, allowing the merger to proceed.

The nature of this case differs from recent successful FTC challenges of hospital mergers in that it involved hospitals in a densely populated area where there are many nearby health care options (Hatzitaskos et al., 2021). In the court's decision, the belief that insurers could easily exclude a consolidated hospital from their networks due to the many possible substitutes in the area was crucial in rejecting the government's argument. If an economic model assumes rational patients, then these patients must necessarily include each of the feasible, densely located hospitals within their consideration sets. If, in reality, Philadelphia patients do not consider all available options, then the number of non-merging substitutes is artificially reduced.

Before simulating the merger using pre-merger data, the realized price effects are estimated for comparison. Table 12 below shows results from merger retrospective price difference-in-differences regressions, using the HCRIS data described in Section 3. Results imply a significant price effect of 17.32-18.05%. Results from robustness checks are in Appendix J. A significant price effect continues to hold when hospital fixed effects are added and when observations with any missing inputs for approximating prices are removed. In each of the twelve total specifications with at least state or county fixed effects, there is a significant price increase relative to controls of at least 12.45%. This demonstrates that the court erred in determining that the proposed merger would not be anti-competitive. Although evidence of the potential for anti-competitive effects presented in court did not meet the necessary burden of proof, the government's initial conjecture has proven to be correct.

Table 9: Merger Retrospective Price Difference-in-Differences

Dependent Variable:	$\ln(\text{Price}_{ht})$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	9.556^{***}			9.561^{***}		
	(0.0132)			(0.0135)		
Post	-0.0159	-0.0160	-0.0112	-0.0176	-0.0175	-0.0131
	(0.0188)	(0.0126)	(0.0149)	(0.0192)	(0.0130)	(0.0152)
Treat	-0.1601	-0.0350^{***}	-0.1418^{**}	-0.1654		
	(0.3962)	(0.0061)	(0.0631)	(0.3980)		
Post × Treat	0.1644	0.1644^{***}	0.1597^{***}	0.1661	0.1659^{***}	0.1616^{***}
	(0.5603)	(0.0126)	(0.0149)	(0.5628)	(0.0130)	(0.0152)
Fixed-effects						
State		Yes	Yes		Yes	Yes
County			Yes			Yes
Fit statistics						
Observations	10,664	10,664	10,664	10,297	10,297	10,297
R^2	8.09×10^{-5}	0.09970	0.35523	9.66×10^{-5}	0.10175	0.36061
Controls	All states	All states	All states	All except PA	All except PA	All except PA

Merger Simulation Results

Merger-induced changes in willingness-to-pay per discharge are simulated for both models for one quarter (January-March 2018) using a 10% random sample with results displayed in Table 13.[49] The percentage change in price is given as the weighted average change across insurance plans, weighted by expected quantity. In each model, the top and bottom half percent of insurer-hospital prices are winsorized. Bargaining results from the full consideration model are necessary here to predict price changes from that model, and are presented in Appendix G. The limited consideration model performs relatively well in that the predicted percentage change in price, 6.74%, more closely aligns with the potential for anti-competitive effects. Contrarily, the full consideration model fails the

[49] A tolerance of $1,000 is used for the fixed point algorithm.

standard "hypothetical monopolist" test that asks if the newly merged firm would be able to profitably increase its price by at least 5%.

These findings indicate that relaxing the assumption that patients necessarily consider all in-network options allows for more accurate predictions of anti-competitive market outcomes. Although other discrete choice methods may allow for unobserved heterogeneity in a full consideration model, such as with a random coefficient on distance (Raval et al., 2022) or prices (Berry et al., 1993), these methods assume unobserved heterogeneity is i.i.d. across options, which prevents the distribution of unobserved heterogeneity from changing in counterfactual scenarios. Instead, this paper endogenizes unobserved heterogeneity in choices through advertising competition. Decomposing the total price effect in the limited consideration model reveals that post-merger shifts in attention are the primary factor driving the predicted price increase, accounting for 68.46% of the total price effect. This decomposition highlights the significance of modeling firms' competition for attention when evaluating hypothetical market interventions in settings with complex products.

Table 10: Predicted Price Effects of the Merger

Model	% Change in Price	% of Total Change From Repositioning
(1) Limited Cons. Model	6.74%	68.46%
(2) Full Cons. Model	2.37%	0%

10 Conclusion

In this paper, I develop a random consideration sets model of hospital demand embedded in a two-stage game of bargaining and advertising. Results show that inattention segments the market, raises prices, and reduces hospital access. I relax the assumption that patients necessarily consider all feasible options, which is ubiquitous to existing discrete choice demand models used for evaluating counterfactual interventions in differentiated product markets. Natural experimental evidence indicates that relaxing this assumption, along with allowing for endogenous post-merger shifts in attention, is essential to accurately predict the potential for anti-competitive effects of a realized merger. These results underscore the importance of integrating behavioral frictions into existing frameworks for analyzing market interactions in imperfectly competitive industries, paving the way for further research in this area.

The viability of structural econometric methods in resolving antitrust conflicts depends on their ability to predict real-world behavior. Restrictive assumptions in standard models can lead to biased substitution patterns and welfare estimates when actual consumer behavior differs from these assumptions. Proponents of integrating behavioral economics into antitrust analysis emphasize the importance of empirical work to support their propositions (Reeves and Stucke, 2011). Likewise, critics point to the practical challenges of applying behavioral insights, arguing that "behavioral antitrust offers no model against which to measure the workings of actual and future markets, no testable conclusions, and no guidelines for advising clients, enforcing the laws, or deciding hard cases" (Devlin and Jacobs, 2014). The model developed in this paper serves as a first step towards addressing these limitations.

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Appendix

A Proposition 1

Proposition 1. *For any insurance plan m and system s with hospitals* $\mathbf{H_s} = \{h_1, h_2, ..., h_N\}$ *indexed in an arbitrary order, the aggregate ex-ante willingness-to-pay to include s within an insurer's complete network* $\mathbf{H}$ *is given as*

$$WTP_m(\mathbf{H_s}|\mathbf{H_m}) \approx \sum_{t\in\mathbf{T}} N_{mt} \int_{Z,K,F} \frac{1}{\alpha_i} \sum_{c\in\boldsymbol{C}_i} pr_{it}(c|\mathbf{v_{it}}) \left(\frac{WTP_{it|c}(h_{min|c}|\mathbf{x_{it}})}{1-\Psi_{it,s}(\mathbf{x_{it}}, \mathbf{v_{it}}|c)} \right) g_{zkf}(\mathbf{z_{it}}, \mathbf{k_{it}}, \mathbf{f_{st}}) d\mathbf{f_{st}} d\mathbf{k_{it}} d\mathbf{z_{it}}.$$

where

$$h_{min|c} = \min \left\{ h \mid h \in \mathbf{H_s} \wedge h \in c \right\}$$

and

$$WTP_{it|c}(h_{min|c}|\mathbf{x_{it}}) = \ln \left(\frac{1}{1 - s_{ih_{min|c}t}(\mathbf{x_{it}}|c)} \right)$$

and

$$\Psi_{it,s}(\mathbf{x_{it}},\mathbf{v_{it}}|c) = \sum_{j\in c\wedge \mathbf{H_{s\setminus\{h_{min|c}\}}}} D_{it,h_{min|c}h_j}(\mathbf{x_{it}},\mathbf{v_{it}}|c)$$

and

$$D_{it,h_{min|c}h_j}(\mathbf{x_{it}},\mathbf{v_{it}}|c) = \frac{s_{ih_jt}(\mathbf{x_{it}}|c)}{1-s_{ih_{min|c}t}(\mathbf{x_{it}}|c)}.$$

Proof. The proof is by induction. We first establish the base case for a N = 1 product firm. Then, we assume that the theorem holds for a firm with some set of products $\mathbf{H}_s = \{h_1,...,h_N\} \subseteq \mathbf{H}$ and aim to show that this implies it must hold for $\mathbf{H}_s = \{h_1,...,h_N,h_{N+1}\} \subseteq \mathbf{H}$. Additionally, we drop the notation for integrating over realized patient characteristics and focus derivations on the willingness-to-pay for some i with realized demographics $\mathbf{k_i}$ and clinical characteristics $\mathbf{z_i}$. Integrating over characteristics and summing over the population will then follow from the derivations in the proof.

Base Case:

First, consider the aggregate willingness-to-pay to include a single hospital h_1 in $\mathbf{H}$. The value to patient i from having hospital h_1 in her network, conditional upon realized clinical characteristics and firm advertising costs is

$$WTP_i(h_1|\mathbf{H_m}) = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\mathbb{E}[\max_{k\in c} u_{ik}(\mathbf{x}_{ik})] - \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\mathbb{E}[\max_{k'\in c_{\setminus\{h_1\}}} u_{ik'}(\mathbf{x}_{ik})], \quad (17)$$

where $c_{\setminus\{h_1\}}$ denotes the set of hospitals in c not including h_1. For all $c \in C$, $\mathbb{E}[\max_{k\in c} u_{ik}]$ has a closed form such that we can express (17) as

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\big(\ln(\sum_{k\in c} exp(\mathbf{x_{ik}}\beta)) - \ln(\sum_{k'\in c_{\setminus\{h_1\}}} exp(\mathbf{x_{ik'}}\beta))\big) = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\ln\Big(\frac{\sum_{k\in c} exp(\mathbf{x_{ik}}\beta)}{\sum_{k'\in c_{\setminus\{h_1\}}} exp(\mathbf{x_{ik'}}\beta)}\Big)\right). \quad (18)$$

We make three observations. First, the individual outside good unconditional choice probability is

$$\sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})s_{i0}(\mathbf{x}_i|c) = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\frac{1}{\sum_{k'\in c} exp(\mathbf{x_{ik'}}\beta)}.$$

Second, the outside good unconditional choice probability after removing h_1 increases by the individual share of h_1 times the diversion ratio from h_1 to the outside good:

$$\sum_{c \in \mathbf{C}_{\mathbf{i}\setminus\{h_1\}}} pr_i(c|\mathbf{v_i}) s_{i0}(\mathbf{x}_i|c) = \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) s_{i0}(\mathbf{x}_i|c) + D_{i,h_1 0}(\mathbf{x}_i|c) s_{ih_1}(\mathbf{x}_i|c).$$

Third, i's diversion ratio from h_1 to the outside option is:

$$\sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) D_{i,h_1 0}(\mathbf{x}_i|c) = \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{s_{i0}(\mathbf{x}_i|c)}{1 - s_{ih_1}(\mathbf{x}_i|c)}.$$

where $D_{i,h_1 0}(\mathbf{x}_i|c)$ is the diversion ratio conditional upon the realization of the consideration set c.

This allows us to express (18) as

$$= \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) \ln \left(\frac{s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1\}})}{s_{i0}(\mathbf{x}_i|c)} \right)$$

$$= \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) \ln \left(\frac{s_{i0}(\mathbf{x}_i|c) + D_{i,h_1 0}(\mathbf{x}_i|c) s_{ih_1}(\mathbf{x}_i|c)}{s_{i0}(\mathbf{x}_i|c)} \right)$$

$$= \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) \ln \left(1 + \frac{s_{ih_1}(\mathbf{x}_i|c)}{1 - s_{ih_1}(\mathbf{x}_i|c)} \right)$$

$$\approx \sum_{c \in \mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{s_{ih_1}(\mathbf{x}_i|c)}{1 - s_{ih_1}(\mathbf{x}_i|c)}. \tag{19}$$

Inductive Hypothesis:

Assume that the theorem holds for the set $\mathbf{H}_s = \{h_1, ..., h_N\} \subseteq \mathbf{H}$. From Equation (18), we have:

$$\frac{WTP_i(h_1,...,h_N,h_{N+1}|\mathbf{H_m})}{WTP_i(h_1,...,h_N|\mathbf{H_m})} = \frac{\sum\limits_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\ln\left(\sum\limits_{j\in c} exp(\mathbf{x_{ij}}\beta)\right) - \ln\left(\sum\limits_{j'\in c_{\setminus\{h_1,...,h_N,h_{N+1}\}}} exp(\mathbf{x_{ij'}}\beta)\right)\right)}{\sum\limits_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\ln\left(\sum\limits_{j\in c} exp(\mathbf{x_{ij}}\beta)\right) - \ln\left(\sum\limits_{j''\in c_{\setminus\{h_1,...,h_N\}}} exp(\mathbf{x_{ij''}}\beta)\right)\right)}$$

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\ln\left(\sum_{j''\in c\setminus\{h_1,...,h_N\}} exp(\mathbf{x_{ij''}}\beta)\right) - \ln\left(\sum_{j'\in c\setminus\{h_1,...,h_N,h_{N+1}\}} exp(\mathbf{x_{ij'}}\beta)\right)\right)$$

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\frac{s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N,h_{N+1}\}})}{s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}\right). \qquad (20)$$

Note that $s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N,h_{N+1}\}}) = s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}}) + D_{i,h_{N+1}0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})$. Then (20) can be expressed as

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(1 + \frac{D_{i,h_{N+1}0}(\mathbf{x}_{it}|c_{\setminus\{h_1,...,h_N\}})s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}{s_{i0}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}\right)$$

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(1 + \frac{s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}{1 - s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}\right)$$

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\left(\frac{1}{1 - s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}})}\right). \qquad (21)$$

where the second equality results from writing out the diversion ratio $D_{i,h_{N+1}0}(\mathbf{x}_{it}|c_{\setminus\{h_1,...,h_N\}})$ and simplifying. Next, note that

$$s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_N\}}) = s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_{N-1}\}}) + D_{i,h_N,h_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_{N-1}\}})s_{ih_N}(\mathbf{x}_i|c_{\setminus\{h_1,...,h_{N-1}\}})$$

$$= s_{ih_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})\Big(1+\frac{s_{ih_N}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})}{1-s_{ih_N}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})}\Big) = D_{i,h_Nh_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}}). \tag{22}$$

Hence, combining our results from (20), (21), and (22), we now have the following simplified equation for the ratio of WTPs for the N and $N+1$ product firms:

$$\frac{WTP_i(h_1,\ldots,h_N,h_{N+1}|\mathbf{H_m})}{WTP_i(h_1,\ldots,h_N|\mathbf{H_m})} = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\Big(\frac{1}{1-D_{i,h_Nh_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})}\Big). \tag{23}$$

Continuing with this process, note that

$$D_{i,h_Nh_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}}) = \frac{s_{i,h_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})}{1-s_{i,h_N}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}})},$$

where

$$s_{i,h_\eta}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-1}\}}) = s_{i,h_\eta}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}}) + D_{i,h_{N-1},h_\eta}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})s_{i,h_{N-1}}(c_{\setminus\{h_1,\ldots,h_{N-2}\}})$$

$$= s_{i,h_\eta}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})\Big(1+\frac{s_{i,h_{N-1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})}{1-s_{i,h_{N-1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})}\Big)$$

$$= \frac{s_{i,h_\eta}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})}{1-s_{i,h_{N-1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})} = D_{i,h_{N-1},h_\eta}(\mathbf{x}_i|c_{\setminus h_1,\ldots,h_{N-1}}),$$

for $\eta = N, N+1$. Hence, from (23), we now have:

$$\frac{WTP(h_1,\ldots,h_N,h_{N+1}|\mathbf{H_m})}{WTP(h_1,\ldots,h_N|\mathbf{H_m})} = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i})\frac{1}{1-\frac{D_{i,h_{N-1},h_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})}{1-D_{i,h_{N-1},h_N}(c_{\setminus\{h_1,\ldots,h_{N-2}\}})}}$$

$$= \sum_{c\in C} pr_i(c)\frac{1-D_{i,h_{N-1},h_N}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})}{1-D_{i,h_{N-1},h_N}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})-D_{i,h_{N-1},h_{N+1}}(\mathbf{x}_i|c_{\setminus\{h_1,\ldots,h_{N-2}\}})},$$

from which it is clear that continuing this simplification process done above for h_N and h_{N-1} for $h_{N-2},...,h_1$ results in the following:

$$\frac{WTP(h_1,...,h_N,h_{N+1}|\mathbf{H_m})}{WTP(h_1,...,h_N|\mathbf{H_m})} = \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c)}{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c) - D_{i,h_1,h_{N+1}}(\mathbf{x}_i|c)}. \tag{24}$$

Recall that from our inductive hypothesis, we have assumed the theorem holds for an N-product firm. That is, we know the following holds:

$$WTP_i(h_1,...,h_N|\mathbf{H_m}) \approx \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{WTP_i(h_1|c)}{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c)}. \tag{25}$$

Plugging (25) into (24) and rearranging yields:

$$WTP_i(h_1,...,h_N,h_{N+1}|\mathbf{H_m}) \approx \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{WTP_i(h_1|c)}{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c)} \frac{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c)}{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c) - D_{i,h_1,h_{N+1}}(\mathbf{x}_i|c)}$$

$$= \sum_{c\in\mathbf{C_i}} pr_i(c|\mathbf{v_i}) \frac{WTP_i(h_1|c)}{1 - D_{i,h_1,h_2}(\mathbf{x}_i|c) - ... - D_{i,h_1,h_N}(\mathbf{x}_i|c) - D_{i,h_1,h_{N+1}}(\mathbf{x}_i|c)}.$$

Therefore, the inductive hypothesis is proven because if the proposition holds for an N-product firm, it must also hold for an $N+1$-product firm.

□

B First-Order Conditions

Equation (11) shows the first-order condition of any system s's profit function with respect to the advertising expenditure, a_{ht}, for some $h \in \mathbf{H_s}$. h chooses ad expenditure each period by setting the following equal to zero:

$$\frac{\partial \Pi_{st}}{\partial a_{ht}} = \frac{\partial}{\partial a_{ht}} \zeta \sum_{m'\in\mathbf{M}} N_{m't} \int_{Z,K} \frac{1}{\alpha_i} \sum_{c\in\mathbf{C_i}} pr_{it}(c|\mathbf{v}_{it}) \ln\left(\frac{1}{1 - \sum_{h\in\mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c)}\right) g_{zk}(\mathbf{z_{it}},\mathbf{q_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$-\frac{\partial}{\partial a_{ht}}\zeta\theta_{mc}\sum_{m'\in\mathbf{M}}N_{m't}\int_{Z,K}\sum_{c\in\mathbf{C_i}}pr_{it}(c|\mathbf{v}_{it})\big(\sum_{h\in\mathbf{H_s}}s_{iht}(\mathbf{x_{it}}|c)\big)g_{zk}(\mathbf{z_{it}},\mathbf{q_{it}})d\mathbf{k_{it}}d\mathbf{z_{it}}$$

$$-mc^{ad}_{ht}(a_{ht}) \tag{26}$$

$$=\zeta\sum_{m'\in\mathbf{M}}N_{m't}\int_{Z,K}\frac{1}{\alpha_i}\sum_{c\in\mathbf{C_i}}\frac{\partial pr_{it}(c|\mathbf{v}_{it})}{\partial a_{ht}}\ln\left(\frac{1}{1-\sum_{h\in\mathbf{H_s}}s_{iht}(\mathbf{x_{it}}|c)}\right)g_{zk}(\mathbf{z_{it}},\mathbf{q_{it}})d\mathbf{k_{it}}d\mathbf{z_{it}}$$

$$-\zeta\theta_{mc}\sum_{m'\in\mathbf{M}}N_{m't}\int_{Z,K}\sum_{c\in\mathbf{C_i}}\frac{\partial pr_{it}(c|\mathbf{v}_{it})}{\partial a_{ht}}\big(\sum_{h\in\mathbf{H_s}}s_{iht}(\mathbf{x_{it}}|c)\big)g_{zk}(\mathbf{z_{it}},\mathbf{q_{it}})d\mathbf{k_{it}}d\mathbf{z_{it}}$$

$$-mc^{ad}_{ht}(a_{ht}). \tag{27}$$

$\frac{\partial pr_{it}(c|\mathbf{v}_{it})}{\partial a_{ht}}$ from (27) is as follows:

$$\frac{\partial pr_{it}(c|\mathbf{v}_{it})}{\partial a_{ht}}=\frac{\partial\left\{\prod_{j\in c}\phi_{ijt}(\mathbf{v}_{ijt})\prod_{j'\notin c}(1-\phi_{ij't}(\mathbf{v}_{ij't})\right\}}{\partial a_{ht}}$$

$$=\prod_{j\in c}\phi_{ijt}(\mathbf{v}_{ijt})\prod_{j'\notin c}(1-\phi_{ij't}(\mathbf{v}_{ij't})\frac{\partial\phi_{iht}(\mathbf{v}_{iht})}{\partial a_{ht}}\left(\mathbf{I}(h\in c)\frac{1}{\phi_{iht}(\mathbf{v}_{iht})}-(1-\mathbf{I}(h\in c))\frac{1}{1-\phi_{iht}(\mathbf{v}_{iht})}\right).$$

Note that

$$\frac{\partial(\phi_{iht}(\mathbf{v}_{iht}))}{\partial a_{ht}}=\frac{\partial(\mathbf{v}_{iht}\tau)}{\partial a_{ht}}\phi_{iht}(\mathbf{v}_{iht})(1-\phi_{iht}(\mathbf{v}_{iht})).$$

Plugging this into Equation (27) yields the FOC

$$\frac{\partial \Pi_{st}}{\partial a_{ht}} = \zeta \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \frac{1}{\alpha_i} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \frac{\partial (\mathbf{v_{iht}} \tau)}{\partial a_{ht}} \Bigg(\mathbf{I}(h \in c)(1-\phi_{iht}(\mathbf{v_{iht}})) - (1-\mathbf{I}(h \in c))\phi_{iht}(\mathbf{v_{iht}}) \Bigg) \ln \Bigg(\frac{1}{1 - \sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c)} \Bigg) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$-\zeta \theta_{mc} \sum_{m' \in \mathbf{M}} N_{m't} \int_{Z,K} \sum_{c \in \mathbf{C_i}} pr_{it}(c|\mathbf{v_{it}}) \frac{\partial (\mathbf{v_{iht}} \tau)}{\partial a_{ht}} \Bigg(\mathbf{I}(h \in c)(1-\phi_{iht}(\mathbf{v_{iht}})) - (1-\mathbf{I}(h \in c))\phi_{iht}(\mathbf{v_{iht}}) \Bigg) \Big(\sum_{h \in \mathbf{H_s}} s_{iht}(\mathbf{x_{it}}|c) \Big) g_{zk}(\mathbf{z_{it}}, \mathbf{k_{it}}) d\mathbf{k_{it}} d\mathbf{z_{it}}$$

$$-mc^{ad}_{ht}(a_{ht}). \tag{28}$$

C Proof of Proposition 2

Proof. Fix any i. By rearranging Equation (4), we have

$$s_{ih}(\mathbf{x_i}, \mathbf{v_i}) = \underbrace{\phi_{ih}(\mathbf{v}_{ih})}_{\text{Depends on } \tilde{a}_h} \underbrace{\sum_{c \in \mathbf{C_i}} pr_i\big(c|\mathbf{v_i}\big) s_{ih}(\mathbf{x_i}|c)}_{\text{Does not depend on } \tilde{a}_h}.$$

Taking the natural logs:

$$\ln\big(s_{ih}(\mathbf{x_i}, \mathbf{v_i})\big) = \ln\big(\phi_{ih}(\mathbf{v}_{ih})\big) + \ln\Bigg(\sum_{c \in \mathbf{C_i} \setminus \{h\}} pr_i\big(c|\mathbf{v_i}, h \in C\big) s_{ih}(\mathbf{x_i}|c)\Bigg),$$

and then the partial derivative with respect to $\tilde{a}_h$:

$$\frac{\partial \ln\big(s_{ih}(\mathbf{x_i}, \mathbf{v_i})\big)}{\partial \tilde{a}_h} = \frac{\partial \ln\big(\phi_{ih}(\mathbf{v}_{ih})\big)}{\partial \tilde{a}_h} + 0.$$

By the fundamental theorem of calculus, this can be rearranged to obtain the following expression for $\phi_{ih}(\mathbf{v}_{ih})$:

$$\phi_{ih}(\mathbf{v}_{ih}) = exp\Bigg(\int_{\tilde{a}_h}^{\bar{a}_h} \frac{\partial \ln\big(s_{ih}(\mathbf{x_i}, \mathbf{v_i})\big)}{\partial \tilde{a}_h} d\tilde{a}_h \Bigg)$$

Doing so $\forall h \in \mathbf{H}$ identifies the consideration set probabilities. $\square$

D Discussion of Demand Model in Relation to Previous Literature

As reviewed in Section 3, results from Raval et al., 2022 suggest that allowing for more flexible unobserved patient-level heterogeneity by adding a random coefficient on distance improves model performance. A patient's utility in their model, simplified by only including alternative specific constants and a distance term d_{ih}, is[50]

$$u^*_{ih} = \alpha_h + \beta_i d_{ih} + \varepsilon_{ih}, \tag{29}$$

where the coefficient on distance varies across individuals: $\beta_i \sim f(\beta)$, and parameters of $f(\beta)$ are estimated. In this model, the patient knows the values of β_i and ε_i and chooses h if and only if $u^*_{ih} > u^*_{ih'} \forall h' \in \mathbf{H}_i$. The intuition for why this predicts substitution patterns better than compared models is as follows. If some patient i has an observed long travel distance in choosing hospital h, then if h is no longer available, the random-coefficients model allows for i to be more likely to substitute to other far away hospitals for reasons that cannot be explained by observed heterogeneity in willingness-to-travel.

To see how the random consideration model compares to this, note that it generates choice probabilities that would be equivalent to a full consideration model based on the following indirect utility function:

$$u^*_{ih} = \alpha_h + \beta d_{ih} + \varepsilon_{ih} + \gamma_{ih}, \tag{30}$$

where

$$\gamma_{ih} = \begin{cases} 0 & \text{with prob. } \phi_{ih} \\ -\infty & \text{with prob. } 1 - \phi_{ih}. \end{cases}$$

[50]We denote by a star any equation used as a motivating example and not a formal description of the model.

Equation (30) would predict the same substitution patterns as a random consideration sets model with each option being considered with independent probability ϕ_{ih}. γ_{ih} is allowed to vary with rich heterogeneity captured by the consideration probability. In a random coefficient model, the unobserved characteristics are taken to be i.i.d. across alternatives and can be interpreted as additive noise capturing a consumer's idiosyncratic willingness-to-travel. However, unobserved heterogeneity may affect choices mostly through consideration which, as shown in Equation (30), is consistent with a full consideration discrete choice model with an additive error that is independent across alternatives, but not identically so (Barseghyan et al., 2021). This allows for a given consumer to face unobserved heterogeneity that is distributed differently across options. This unobserved heterogeneity is endogenized by hospital advertising competition in order to assess how it will change in market counterfactuals.

E Reduced-Form Evidence Robustness Checks

Table 11: Varying Impact of Advertising On Market Shares Depending on Prior Brand Familiarity

	Dependent variable:		
	Mkt. Shr.$_{zht}$		
	(1)	(2)	(3)
$\ln(1+a_{ht})$	0.542^{***}	0.485^{***}	0.433^{***}
	(0.101)	(0.100)	(0.099)
I(System Hospital $<$ 5 Miles)$_{zh}$	-0.101		
	(0.619)		
I(System Hospital $<$ 10 Miles)$_{zh}$		-1.527^{**}	
		(0.625)	
I(System Hospital $<$ 15 Miles)$_{zh}$			-1.508^{**}
			(0.724)
Distance$_{zh}$	-0.132^{***}	-0.132^{***}	-0.129^{***}
	(0.016)	(0.015)	(0.015)
$\ln(1+a_{ht})\times$I(System Hospital $<$ 5 Miles)$_{zh}$	-0.932^{***}		
	(0.163)		
$\ln(1+a_{ht})\times$I(System Hospital $<$ 10 Miles)$_{zh}$		-0.603^{***}	
		(0.147)	
$\ln(1+a_{ht})\times$I(System Hospital $<$ 15 Miles)$_{zh}$			-0.367^{**}
			(0.172)
$\ln(1+a_{ht})\times$Distance	0.025^{***}	0.028^{***}	0.029^{***}
	(0.004)	(0.004)	(0.004)
Observations	6,363	6,363	6,363
R^2	0.392	0.394	0.388

Note: OLS, Hospital FEs included

F Monte Carlo Experiment

In this section, I examine how a full consideration model would estimate the diversion ratios of data simulated from a random consideration data generating process. The set **J** = {1, 2, ..., J} denotes the set of all hospitals that can be considered, with $|\mathbf{J}| = 10$. Hospitals 1 and 2 belong to a single system and advertise together. Hospitals 3-9 are stand-alone hospitals and advertise separately. Choice option 10 is the outside option and has utility normalized to 0.

The utility that individual i obtains from choosing an inside hospital j is

$$u_{ij}^{MC} = \beta_1 x_{ij,1} + \beta_2 x_{ij,2} + \varepsilon_{ij}$$

where x_{ij1}, $x_{ij2} \sim N(3,2)$, $\varepsilon_{ij} \sim EV-1(0,1)$, and β_1 and β_2 are parameters.[51] Outside utility is normalized as $u_{i0} = \varepsilon_{i0}$.

Each i considers the outside option with probability 1 and searches the other $J-1$ hospitals using the following algorithm:

1. Draw a vector of random variables $\omega_{ij} = (\omega_{i1}, ..., \omega_{iJ})$ where $\omega_{ij} \sim U[0,1]$.
2. For each j, include j in i's consideration set $\mathbf{C_i}$ iff $\phi_{ij} > \omega_{ij}$ where ϕ_{ij} is the consideration prob.

$$\phi_{ij} = \frac{exp[x_{ij,3}\gamma_1 + x_{ij2}\gamma_2]}{1 + exp[x_{ij,3}\gamma_1 + x_{ij,2}\gamma_2]},$$

where $x_{ij3} \sim N(3,1)$ and $\gamma_1 = 3$ is a parameter. We can interpret $x_{ij,1}$ and $x_{ij,2}$ as two variables that affect utility (i.e. clinical quality and travel distance). $x_{ij,3}$ can be interpreted as a consideration shifting variable, such as the hospital's advertising stock. i's realized choice probability of j is then

$$\frac{exp(\beta_1 x_{ij,1} + \beta_2 x_{ij,2})}{\sum_{k \in \mathbf{C_i}} exp(\beta_1 x_{ik,1} + \beta_2 x_{ik,2})}$$

[51] In the results below, $\beta_1 = 2$ and $\beta_2 = -1$

whereas the full-consideration model would estimate choice probabilities as:

$$\frac{exp(\tilde{\beta}_1 x_{ij,1} + \tilde{\beta}_2 x_{ij,2})}{\sum_{k \in \mathbf{J}} exp(\tilde{\beta}_1 x_{ik,1} + \tilde{\beta}_2 x_{ik,2})}$$

In the Monte Carlo model, system hospitals 1 and 2 “advertise" together (the draws $x_{i1,3} = x_{i2,3}$). This experiment is implemented to show that the full consideration model is biased when the data is generated from a limited consideration model. The table below shows results for the full and limited consideration estimates. The full consideration model underestimates the diversion from 1 to system member 2 by roughly 2%. Each individual's diversion ratio is weighted when summing to get the aggregate diversion ratio between any two options (Conlon and Mortimer, 2021). Specifically, each individual's weight is equal to i's unconditional probability of choosing the excluded option over the sum of all individuals' unconditional probabilities of choosing the excluded option.

Table 12: Monte Carlo Results

	Full cons.	Limited cons.
$D_{1,2}$	**0.12**	**0.14**
$D_{1,3}$	0.12	0.11
$D_{1,4}$	0.12	0.10
$D_{1,5}$	0.12	0.11
$D_{1,6}$	0.12	0.11
$D_{1,7}$	0.12	0.10
$D_{1,8}$	0.12	0.11
$D_{1,9}$	0.12	0.11
$D_{1,10}$	0.05	0.11

G Additional Bargaining Results

Table 13: Bargaining First Stage Results

	(OLS)
Intercept	-0.3104
	(0.2090)
ln(Number of Inpatient Beds$_s$)	0.1771***
	(0.0321)
Observations	102
R^2	0.234

Table 14: Bargaining Results: Full Consideration Model

	(OLS)
Intercept	6.175***
	(1.293)
WTP per weighted discharge	6.670***
	(1.780)
Observations	133
R^2	0.097

H Marginal Cost of Advertising: First-Stage Results

Table 15: First Stage Results

	(1)
(Intercept)	0.1040
	(0.4542)
$\ln(1+a_{ht-1})$	0.9107***
	(0.1020)
Observations	50
R^2	0.624
Hospital FEs	No

I Full Consideration Demand Results

Table 16: Full Consideration Model: Demand Results

Variable	**Coefficient**	**Standard Error**
	Utility Variables	
Distance	-1.3424	0.0317
Distance * Severity	5.9829	0.9351
Distance * Income	0.0638	0.0066
I(Hospital 1)	4.4023	0.1589
I(Hospital 2)	4.5751	0.1598
I(Hospital 3)	3.3040	0.1784
I(Hospital 4)	5.5157	0.1590
I(Hospital 5)	7.7039	0.1631
I(Hospital 6)	4.6904	0.1616
I(Hospital 7)	3.0766	0.1742
I(Hospital 8)	3.7226	0.1678
I(Hospital 9)	4.2853	0.1641
I(Hospital 10)	3.4638	0.1723
I(Hospital 11)	4.0421	0.1673
I(Hospital 12)	5.6142	0.1583
I(Hospital 13)	4.7462	0.1514
I(Hospital 14)	5.6943	0.1585
I(Hospital 15)	3.9757	0.1621
I(Hospital 16)	5.3964	0.1796

J Merger Retrospective Price Difference-in-Differences Robustness Checks

Table 17: Merger Retrospective Price Difference-in-Differences (Adding Hospital Fixed Effects

Dependent Variable:				$\ln(\text{Price}_{ht})$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post	0.0079	0.0108	0.0096	0.0055	0.0086	0.0074
	(0.0070)	(0.0069)	(0.0077)	(0.0072)	(0.0070)	(0.0079)
Post × Treat	0.1405***	0.1377***	0.1389***	0.1430***	0.1399***	0.1411***
	(0.0373)	(0.0374)	(0.0407)	(0.0373)	(0.0374)	(0.0408)
Fixed-effects						
Hospital	Yes	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes		Yes	Yes
County			Yes			Yes
Fit statistics						
Observations	10,664	10,664	10,664	10,297	10,297	10,297
R^2	0.95122	0.95379	0.95794	0.95082	0.95343	0.95766
Controls	All states	All states	All states	All except PA	All except PA	All except PA

Table 18: Merger Retrospective Price Difference-in-Differences (Restricted Sample With No Missing Values)

Dependent Variable:				$\ln(\text{Price}_{ht})$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	9.229***			9.235***		
	(0.0137)			(0.0141)		
Post	0.0276	0.0320**	0.0378**	0.0236	0.0288*	0.0342*
	(0.0198)	(0.0150)	(0.0166)	(0.0203)	(0.0155)	(0.0174)
Treat	0.0268	0.1284***	0.1850***	0.0208		
	(0.2372)	(0.0066)	(0.0601)	(0.2377)		
Post × Treat	0.1217	0.1173***	0.1561***	0.1257	0.1205***	0.1551***
	(0.3557)	(0.0150)	(0.0213)	(0.3564)	(0.0155)	(0.0174)
Fixed-effects						
State		Yes	Yes		Yes	Yes
County			Yes			Yes
Fit statistics						
Observations	2,863	2,863	2,863	2,750	2,750	2,750
R^2	0.00081	0.17285	0.54166	0.00062	0.17751	0.55033
Controls	All states	All states	All states	All except PA	All except PA	All except PA

K Summary Statistics for Major Diagnostic Categories

Table 19: Patient MDC Summary Statistics, 2017-2018

Variable	N	%
MDC	54,528	
... Nervous System	4,849	9%
... Eye	244	0%
... Ear, Nose, Mouth And Throat	1,138	2%
... Respiratory System	4,012	7%
... Circulatory System	4,762	9%
... Digestive System	5,120	9%
... Hepatobiliary System And Pancreas	1,761	3%
... Musculoskeletal System And Connective Tissue	5,833	11%
... Skin, Subcutaneous Tissue And Breast	1,408	3%
... Endocrine, Nutritional And Metabolic System	2,806	5%
... Kidney And Urinary Tract	1,822	3%
... Male Reproductive System	568	1%
... Female Reproductive System	1,029	2%
... Pregnancy, Childbirth And Puerperium	6,668	12%
... Blood and Blood Forming Organs and Immunological Disorders	1,083	2%
... Myeloproliferative DDs (Poorly Differentiated Neoplasms)	1,754	3%
... Infectious and Parasitic DDs	2,590	5%
... Mental Diseases and Disorders	2,584	5%
... Alcohol/Drug Use or Induced Mental Disorders	1,402	3%
... Injuries, Poison And Toxic Effect of Drugs	1,029	2%
... Burns	96	0%
... Factors Influencing Health Status	437	1%
... Multiple Significant Trauma	116	0%
... Human Immunodeficiency Virus Infection	65	0%
... Ungroupable	1,352	2%

L Hospital IDs and Names

Table 20: Hospital IDs and Names

Hospital ID	**Hospital Name**
1	Albert Einstein Medical Center
2	Temple University Hospital
3	Methodist Hospital
4	Pennsylvania Hospital of the University of Pennsylvania Health System
5	Children's Hospital of Philadelphia
6	Penn Presbyterian Medical Center
7	Nazareth Hospital
8	Jeanes Hospital
9	Hahnemann University Hospital
10	Chestnut Hill Hospital
11	Mercy Philadelphia Hospital
12	Thomas Jefferson University Hospital, Inc.
13	Aria Health
14	Hospital of the University of Pennsylvania
15	Hospital of Fox Chase Cancer Center
16	St. Christopher's Hospital for Children
0	Outside Option

M Distance Elasticities

Let $E_{i,h}$ denote the elasticity of the probability that i chooses h with respect to the distance d_{ih}:

$$E_{ih} = \frac{\partial s_{ih}}{\partial d_{ih}} \frac{d_{ih}}{s_{ih}}.$$

First, note that

$$s_{ih} = \phi_{ih} \sum_{c \in \mathbf{C_i}} pr_i(c \mid h \in c) s_{ih|c}.$$

From which we have

$$\frac{\partial s_{ih}}{\partial d_{ih}} = \frac{\partial u_{ih}}{\partial d_{ih}} \sum_{c \in \mathbf{C_i}} pr_i(c) s_{ih|c}(1 - s_{ih|c}) + \frac{\partial A_{ih}}{\partial d_{ih}}(1 - \phi_{ih}) \sum_{c \in \mathbf{C_i}} pr_i(c) s_{ih|c},$$

such that

$$E_{ih} = d_{ih} \frac{\partial A_{ih}}{\partial d_{ih}}(1 - \phi_{ih}) + \frac{\partial u_{ih}}{\partial d_{ih}} \frac{d_{ih}}{s_{ih}} \sum_{c \in \mathbf{C_i}} pr_i(c) s_{ih|c}(1 - s_{ih|c}).$$

Next, let E_{ih}^{FC} denote the full consideration model's elasticity of the probability that i chooses h with

$$\frac{\partial s_{ih}^{FC}}{\partial d_{ih}} = \frac{\partial u_{ih}}{\partial d_{ih}} s_{ih}^{FC}(1 - s_{ih}^{FC}).$$

Then we have

$$E_{ih}^{FC} = \frac{\partial u_{ih}}{\partial d_{ih}} d_{ih}(1 - s_{ih}^{FC}).$$

N Summary Statistics for Auxiliary Insurance Claims Data

Table 21: Quarterly Health Shock Rates for Demographic Groups

Demographic Cell	Quarterly Shock Rate, 2017-2018
Female, 0-19	0.0039
Female, 20-34	0.0206
Female, 35-45	0.0145
Female, 46-54	0.0115
Female, 55-64	0.0193
Male, 0-19	0.0033
Male, 20-34	0.0046
Male, 35-45	0.0058
Male, 46-54	0.0107
Male, 55-64	0.0205

Table 22: Quarter-Group Enrollment and Utilization

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Number of Enrollees in Demographic Group, Quarterly	40	938,247	177,011	666,766	810,859	1,053,082	1,264,270
Number of Enrollees w/ Inpatient Hospital Admission in Demographic Group, Quarterly	40	10,288	6,412	3,716	4,641	13,419	25,397