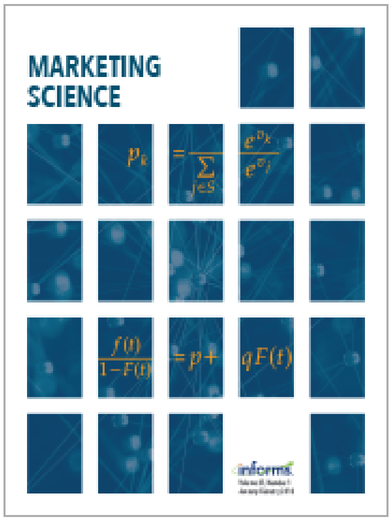

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Expert's Recommendations in Product Choices: Information Provision, Conflicts of Interest, and Consumer Protection among U.S. Kidney Disease Patients

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Abstract. Consumers in high-stakes product markets, such as healthcare or finance, often rely on experts' recommendations before making a purchase decision. However, how an expert constructs a specific set of recommendations and how it subsequently affects consumer choices and outcomes have been understudied. We propose an empirical framework that econometrically recovers experts' recommendations and combines them with heterogeneous consumers' choice of products or services. We then apply the framework to examine kidney disease patients' choice of dialysis facilities. Using detailed data on more than 16,900 U.S. patients with kidney disease who had consultations with over 750 physicians between 2015 and 2017, we study physicians' dialysis facility recommendations and patients' subsequent choice of facilities. We find that physicians are more likely to recommend facilities with which they are affiliated and those close to patients. Policy simulations suggest that quality information provision through five-star ratings has likely lowered mortality, thereby helping patients. In contrast, reducing conflicts of interest by banning the usage of affiliation as a basis for physicians' facility recommendations can inadvertently hurt patients as evidenced by an increase in mortality. The study provides relevant consumer-centric insights into recent efforts to change market regulations and policies in this healthcare market.

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Disclaimer: The data reported here have been supplied by the United States Renal Data System (USRDS). The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy or interpretation of the U.S. government.

Keywords: expert recommendation • information provision • conflicts of interest • consumer protection • healthcare • structural model

1. Introduction

Consumers often rely on the advice and recommendations of professional experts before making purchase decisions. This tendency is more prevalent in markets involving complex and high-stakes decisions for which consumers have little familiarity, knowledge, skill, or confidence, such as retail financial services, insurance policies, mortgages, automobile repairs, and medical care. Given the complexity of these products, considerable expertise is required to make an informed decision, highlighting the need for intermediary experts—such as stock advisors in the financial market and physicians in the healthcare market—who help consumers by providing recommendations (Schwartz et al. 2011).

This intermediation of experts has been examined in the extant literature from the perspective of information provision (Özer et al. 2018) and conflicts of interest (Dulleck and Kerschbamer 2006, Inderst and Ottaviani 2009). Other research has also investigated this phenomenon with a focus on the evaluation of policy interventions, such as mandatory disclosure laws, aimed at reducing the latter to protect consumers (Anagol et al. 2017, Charoenwong et al. 2019).

However, how experts construct a specific set of recommendations and how this subsequently affects consumer choices and outcomes have been understudied. Our study aims to investigate the joint decision-making process of heterogeneous experts and consumers in the healthcare market by examining the choice of treatment facilities. We consider joint decision making as a stepwise decision-making process in which an expert with superior knowledge of the market recommends a finite set of facility alternatives and their clients or consumers choose from the recommendation set. Using detailed individual-level data from the United States, we examine how the aforementioned market considerations—information provision, conflicts of interest, and policy interventions—affect experts' recommendations as well as consumer choices and outcomes.

Our research context focuses on patients with advanced chronic kidney disease, specifically end-stage kidney disease (ESKD). These patients require a life-sustaining treatment called hemodialysis (hereinafter dialysis) on a regular basis for survival. According to the Centers for Disease Control and Prevention (CDC), kidney disease is a leading cause of death in the United States, where 360 people begin dialysis treatment for ESKD every 24 hours.[1] This prevalence led to more than $49 billion in Medicare spending for ESKD patients in 2018, accounting for more than 1% of the entire U.S. federal budget.[2]

Patients diagnosed with ESKD face the daunting task of choosing, with the help of a physician, a dialysis treatment facility. Our interviews with physicians revealed that in this process, they first talk to patients to learn about their needs and preferences for dialysis and then offer a shortlist or recommended set of dialysis treatment facilities.[3] Patients then choose a treatment facility based on the physicians' recommendations. Even though the patient's facility choice is typically documented in insurance claims data, the physician's recommendations are not, which is a common empirical challenge in studying consumer choices with expert mediation.

To address this issue, we propose an empirical framework that econometrically recovers the experts' recommendation sets and models heterogeneous consumers' subsequent choice of products or services. The recommendation stage has exclusion restrictions from the patient choice stage, which allows us to identify the recommendations as in Gaynor et al. (2016), Beckert (2018), and Crawford et al. (2021). We then apply this model to detailed data of more than 16,900 U.S. kidney disease patients who had consultations with or were referred by approximately 750 physicians between 2015 and 2017. The data include details on patient demographics (e.g., age, residence zip code, and medical conditions), physician information (e.g., experience, business zip code, and affiliations with treatment facilities), and information on the treatment facilities (e.g., location and ownership type). Using these data, we can track interactions between patients, physicians, and treatment facilities where they receive treatments. Under our framework, when recommending a set of treatment facilities to the patient, physicians consider patient factors, treatment facility characteristics, and their affiliation with nearby treatment facilities as well as their own assessment of a good match between a patient and a treatment facility. With a nonzero cost of recommendation (e.g., the cost of recommending a large set of facilities and explaining them to the patient), the recommendation stage essentially captures physicians' benefit-cost analyses of recommending different sets of treatment facilities. Patients then choose a treatment facility from the list of recommendations.

The estimation results offer several insights into physician recommendations and subsequent patient choices. For example, we find that a physician's affiliation with a dialysis treatment facility—a potential conflict of interest—plays a role in their recommendation. More specifically, physicians are more likely to recommend treatment facilities with which they are associated. Additionally, physicians are more likely to recommend facilities that are closer to patients. Regarding the cost of physician recommendation, we find a lower explanation cost for the facilities with high ratings. However, we do not find the explanation cost to be statistically different between more experienced and less experienced physicians. We find that the patient's choice of facility aligns with expectations; patients prefer facilities with higher star ratings that are closer to their homes. We also observe substantial patient heterogeneity in response to distances and star ratings. For example, we show that African American patients in lower-income areas are less responsive to star ratings. In addition, we observe considerable variance in the match value, indicating significant uncertainty in a physician's assessment of the fit between patients and treatment facilities.

Recovering physician recommendations allows us to conduct counterfactual analyses on policies related to two timely and important topics in this market—information provision and conflicts of interest. In particular, we quantify the impact of policy changes on patient mortality. To mitigate concerns regarding selection bias, we use instrumental variables (IVs) approaches. Furthermore, we deploy an artificial neural network (ANN) framework to improve the precision of our analyses. Additionally, we conducted sensitivity analyses by systematically perturbing the recovered physician recommendations across size, composition, and type of perturbation and found qualitatively consistent results.

Investigating the above issues is relevant for two main reasons. First, recent policy trends, such as Section 3506 of the Affordable Care Act (ACA), encourage a better flow of information in the market to promote medical care that better matches patients' preferences (Oshima Lee and Emanuel 2013). Information provision is particularly more relevant for uncommon but critical medical conditions, such as ESKD, because patients' prior knowledge level is significantly lower than for common illnesses, like colds or flu. We study information provision in the context of Centers for Medicare & Medicaid Services (CMS) five-star ratings. Despite the increasing trend of mandates for quality information provision via star ratings in various healthcare settings, such as dialysis centers, nursing homes, or hospitals, its effectiveness on patient outcomes has been controversial. Although some studies suggest the positive impact of such ratings on patients (e.g., Meyers et al. 2021), others cast doubt on the benefit of the CMS policies mandating these ratings (Tamara Konetzka et al. 2015, Ryskina et al. 2018). In this study, we assess the value of the CMS's dialysis facility star ratings by accounting for its impact on physician recommendations and the resulting patient choices as well as health outcomes. Our counterfactual results show that the absence of this information would result in a range of a 0.03%–0.15% increase in mortality, equivalent to 16–76 additional kidney patient deaths annually, depending on specifications. This underscores the benefits of providing quality information in the market via star ratings, supporting the broader trend toward increasing information availability and transparency in the healthcare market.

Second, a rise in physician affiliation with care facilities in the healthcare market has raised concerns from a consumer protection perspective as potential conflicts of interest can influence patient choice and welfare (Brennan et al. 2006, Guo et al. 2021). This issue is at the center of debate for the current dialysis market, which has prompted calls for regulations. For example, California Proposition 29, which was on the ballot in the 2022 midterm election, was an attempt to mandate the disclosure of physician affiliations with dialysis centers to patients. Although it did not pass, its inclusion on the ballot underscores the prevalence of nondisclosure at the population level and concerns surrounding physician affiliation with dialysis treatment facilities. Although physician affiliation can potentially harm patients by steering them to a suboptimal set of affiliated facilities, it also has the potential to benefit patients from the physician familiarity perspective. Physicians are more familiar with centers to which they are affiliated, which in turn, can potentially result in better care provided to their pool of patients. Therefore, whether physician affiliation harms or benefits patients is an empirical question. Our counterfactual results show that banning affiliation as a basis for recommendations increases the expected mortality by 1.1%, an equivalent of 553 additional kidney patient deaths annually (95% confidence interval (95% CI) = [402, 703]), suggesting that such a policy can hurt patients. This result is partly driven by the fact that physicians in our data are more likely to be affiliated with higher-quality treatment facilities, implying that higher-quality treatment facilities are less likely to be included in recommendations if such a ban is in effect.

From a consumer protection viewpoint, our results suggest that patients may not need to be overly concerned about physician affiliation with treatment facilities as these can improve patient outcomes. This implication, however, needs to be treated cautiously as it is partly driven by the fact that physicians tend to be affiliated with higher-quality treatment facilities. The value of physician affiliation needs to be carefully examined in other circumstances.

Our study offers several managerial implications for healthcare providers. First, our findings show that African American patients in lower-income areas are less responsive to star ratings. This asymmetric response across socioeconomic factors suggests that access to and familiarity with online health resources among disadvantaged groups may influence their engagement with star ratings, despite government mandates to provide such quality information in the market. As primary contact points, healthcare providers may consider promoting user-friendly quality metrics, like star ratings, especially to patients from lower socioeconomic backgrounds to improve their decision making in choosing treatment facilities and ultimately, their health outcomes. Second, we find considerable variance in the match value, indicating significant uncertainty in a physician's assessment of the fit between patients and treatment facilities. Healthcare providers should aim for a shared decision-making process, utilizing tools, such as written materials, videos, or interactive presentations, to better communicate with patients and improve the match (Oshima Lee and Emanuel 2013). Third, it may also be relevant for healthcare systems, such as hospitals or physician groups, to note that physician affiliation can help patients. One physician at a major teaching hospital in the U.S. Southwest revealed to us that their hospital avoids recommending their own treatment facilities because of the perception of conflicts of interest. Our results show that such an internal policy may, in fact, inadvertently harm patients if the affiliated treatment facility is high quality.

This study also offers timely and significant consumer-oriented perspectives into the ongoing public policy debates regarding information provision and conflicts of interest in the healthcare sector. Our counterfactual results demonstrate that policy initiatives encouraging information provision of healthcare provider quality (e.g., Section 3506 of the ACA and the CMS's five-star ratings) can benefit patients by lowering mortality in our context. On the other hand, limiting the use of affiliation as a basis for physician recommendations (e.g., California Proposition 29 in 2022) can hurt patients by potentially increasing mortality.

The rest of the study is organized as follows. We review the literature in Section 2. Section 3 then briefly overviews the kidney care market and patient choice. We provide some descriptive statistics and model-free evidence in Section 4. Section 5 then describes the model specification for the recommendation process and patient choice. Section 5 also lays out the empirical estimation, details of the estimation procedure, and identification argument. Section 6 provides the estimation results, and policy evaluations are presented in Section 7. Finally, Section 8 concludes the study.

2. Related Literature

Our study contributes to the literature examining the role of experts in consumer decision making. In markets with credence goods involving high-stakes decisions, such as financial or healthcare markets, the relationships between experts and consumers and the subsequent impact of these relationships on consumer outcomes are important. For instance, focusing on assistance programs involving both experts and consumers, Özer et al. (2018) study the role of information provision in trustworthiness and its impact on consumer decisions. However, the presence of experts with their own vested interests (i.e., pecuniary interests or conflicts of interest more broadly) raises concerns regarding consumer welfare as they can lead to suboptimal recommendations for consumers. Inderst and Ottaviani (2009) consider the case of misselling in a sales force agency and conclude that there is a high risk of inflating the perceived value of products or recommending an inappropriate product to customers. Dulleck and Kerschbamer (2006) study situations where experts may take advantage of informational asymmetry and provide ways to reduce fraud concerns in the relationship between experts and consumers.

Other studies have evaluated the impact of different policies in the context of conflict of interest. In the realm of fiduciary duties in financial markets, Charoenwong et al. (2019) evaluate the impact of a policy targeting financial advisors that changes the jurisdiction from the federal level to the state level and find that the policy resulted in lower-quality advice for consumers. Anagol et al. (2017) study the life insurance market, where they find that a policy requiring disclosure of expert commissions for some products can lead to those products being recommended less often. In this study, we employ a structural modeling approach to empirically quantify the effect of potential conflicts of interest in recommending healthcare treatment options while also evaluating a policy intervention aimed at addressing these conflicts and measuring its impact on consumer outcomes, particularly in terms of mortality.

Finally, our study contributes to the growing healthcare marketing and economics literature examining consumer choice in the healthcare sector and related implications for quality of care improvement. Although numerous studies examine physician detailing and direct-to-consumer advertising (Narayanan et al. 2004, Manchanda et al. 2008, Liu and Gupta 2011, Ching and Ishihara 2012, Kim and KC 2020a), other healthcare products, such as insurance (Shapiro 2020), hospitals (Kim and KC 2020b, Kim et al. 2023), and high-tech medical procedures (Yoon and Kim 2024), have recently been examined with emphasis on consumer choice. Yoon (2020) also looks at the issue of consumer protection in healthcare. In contrast, we examine consumer choice of treatment facility among kidney disease patients, where experts (i.e., kidney doctors) play a critical role in making recommendations for these credence goods, which consequently affect patient choices and health outcomes downstream.

A limited body of research micromodels the joint decision making of physicians and patients instead of treating them as a single decision-maker unit. Gaynor et al. (2016) study how the quality of care changes with respect to constrained choice sets for cardiac surgery patients in the United Kingdom. They assume that physicians act in the best interest of patients by recommending several options that are above a threshold. In our context, however, physicians do not have certainty about the best option for their patients because of the notion of imperfect information and unobserved match value between the patient and the facility. This aligns with our interviews that physicians care about the idea of "fit" of a center for patients. In addition, physicians tend not to recommend too many centers as explaining all of them to the patients can be time consuming. Therefore, our research explicitly accounts for such costs as well.

Beckert (2018) examines factors that can affect the decision-making process of physicians and patients while accounting for physicians' conflicts of interest as rationing agents on behalf of the public healthcare payer in the United Kingdom. Unlike Beckert (2018), we allow for heterogeneity across recommendations based on patient profile and physician assessment regarding match values. We also extend Beckert (2018) by considering how patients factor in their physicians' rankings of recommended facilities in their choice of treatment facilities. Another key difference from Beckert (2018) is that our study conducts counterfactual analyses to examine how physician affiliation and information provision via quality rating metrics influence physician recommendations and consequently, affect patient health outcomes.

3. Industry Background

This section provides a brief background on ESKD, patient choice of dialysis treatment, and relevant public policies.

3.1. End-Stage Kidney Disease

The first and foremost function of the kidneys is to clean waste products and toxins in the blood and produce urine. Failure of the kidneys to perform these functions results in a condition called uremia, which may lead to dire consequences, such as seizures, coma, or death. Known risk factors for chronic kidney disease include diabetes and high blood pressure. When kidneys cease to function properly in an irreversible way, it is considered the onset of ESKD. These patients' survival relies on two treatment options. The optimal treatment is a kidney transplant. However, because of strict eligibility criteria and a limited supply of deceased and living kidney donors, this option is not a timely treatment option upon diagnosis of ESKD. In fact, less than 20% of ESKD patients are on a kidney transplant waiting list (Melanson et al. 2021). The average waiting time is more than three years for those on the waiting list.

This leaves dialysis as the only viable, timely treatment option for those diagnosed with ESKD. Dialysis is a procedure that mechanically removes waste from the blood. Although at-home dialysis technology exists, approximately 90% of U.S. patients are treated at dialysis treatment facilities (Weiner and Meyer 2020). Therefore, we focus on in-center dialysis or hemodialysis, which involves filtering blood through a machine (dialysis station) outside of the body and then returning it. ESKD patients typically visit a treatment facility three times a week, with each session lasting between three and four hours.

3.2. Dialysis Care Market and Patient Choice

Following the congressional expansion of Medicare in 1972, all ESKD patients are automatically eligible for Medicare dialysis benefits regardless of their age or disability. Treatment facilities are differentiated in terms of location, brand, and service quality. The U.S. dialysis market is dominated by large chains, wherein DaVita and Fresenius account for more than 70% of the market share.[4]

Finding a treatment facility that aligns with patients' values is crucial because of the frequency of dialysis visits throughout a patient's life or until a successful kidney transplant occurs. Given the intensity of treatment, patients diagnosed with ESKD consult with physicians, nephrologists in particular, to discuss their dialysis treatment. Our interviews with physicians revealed that they first talk to the patient to learn about their preferences and values in seeking treatment. The physicians then typically recommend a small set of treatment facilities based on the conversation as well as their own expert knowledge about treatment facilities. Physicians then spend some time explaining different facilities to patients who usually have little prior knowledge about facilities, let alone the process of dialysis.

Although the recommendations are not observed, our study infers the recommendations with an assumption that patients ultimately choose one of the recommended treatment facilities to start their dialysis. This assumption has been made in other healthcare settings (e.g., Gaynor et al. 2016). Furthermore, interviews with physicians suggest that this assumption is reasonable for two reasons. First, dialysis is a credence good with critical health outcomes unlike treatment for common illnesses, like colds or flu. Therefore, it is difficult for patients to disregard physicians' recommendations. Second, we focus our attention on new dialysis patients whose prior knowledge level is assumed to be minimal, making them again unlikely to choose a treatment facility that is not recommended.

4. Data

We requested and obtained ESKD patient data between July 2015 and December 2017 from the U.S. Renal Data System (USRDS) (U.S. Renal Data System 2023). USRDS is a National Institutes of Health-funded national data system that acts as a data warehouse for ESKD patients and collects a large amount of data from various sources, such as the CMS, the Organ Procurement and Transplantation Network, the CDC, and the U.S. Census among others. USRDS processes these various data sources to create a more coherent set of data sets, such as patient, institutional claims, physician/supplier claims, transplant files, and dialysis facilities. In Online Appendix A, we describe each data set in detail and explain how we merged them to construct the study sample.

4.1. Data Overview

The resulting data contain the following information: the visit at which a patient received the diagnosis of ESKD, the physician who the patient saw, and the treatment facility that the patient first chose. Beyond the dates of every relevant interaction and other incidents, our data contain information on various characteristics of patients, their referring physicians, and treatment facilities. This section provides a detailed overview of each data component.

4.1.1. Patients. We use the patient data to identify the age at the onset of dialysis, gender, race, comorbidities, and residential zip code. In order to measure the presence of severe medical conditions, we use a variation of the widely used Charlson Comorbidity Index that is tailored for dialysis patients (Liu et al. 2010). We also use the 2015 Internal Revenue Service Statistics of Income data to approximate the patient income level based on the residential zip code. Our data also include information on medical visits for Medicare patients. It is noteworthy that Medicare covers all ESKD patients and that there is little variation in service charges for Medicare patients.[5] In order to track the referring physician before the first dialysis treatment, we focus on patients with Medicare prior to dialysis treatment.

4.1.2. Physicians. On the physician side, we observe the date and medical details of patient visits and physician characteristics, such as their specialty and practice address. We obtain physician medical experience by combining our data with the National Doctors and Clinicians data using the national provider identifier.[6] We observe in the data whether a physician is affiliated with one or more nearby treatment facilities by working as an attending physician. For each patient, we identify the referring physician recommending treatment facilities by examining the record of the last visit with a nephrologist (kidney specialist with specialty code 39) prior to the initial dialysis session. As we later explain in Section 5.3.2, sufficient variation in each physician's patient pool is needed to identify their recommendation patterns. Therefore, we focus our attention on physicians with a minimum of 20 patients in the data.

4.1.3. Treatment Facilities. We observe the characteristics of each treatment facility, such as the address, ownership structure, and dialysis quality measures. As each physician/patient decides on the treatment facility among nearby facilities, it is important to have quality measures for each treatment facility. We construct two quality metrics specific to the dialysis market: (a) dialysis adequacy and (b) anemia management. Dialysis adequacy refers to how much urea is cleaned from blood during a dialysis session, which is known as the urea reduction ratio (URR). Anemia management is determined by the level of patient hemoglobin (HGB) after dialysis. In addition to dialysis-related measures, we consider mortality, an important factor that reflects the quality of treatment provided by facilities. Section 4.3 and Online Appendix B provide details on how we construct these quality measures.

Note that patients often lack access to these complex quality metrics or find it difficult to interpret them (e.g., Beckert 2018). Understanding complex risk-adjusted measures, such as URR and HGB, is particularly challenging for kidney patients who tend to be older and vulnerable. To address this issue, the CMS launched five-star ratings in 2015.[7] The goal is to make "quality information easy to access and understand for consumers" and to help them to "have a better understanding of the care they receive." Patients can now enter a zip code into the website and browse five-star ratings of nearby treatment facilities, which are a weighted average of various quality metrics, such as dialysis adequacy and mortality rates.[8]

4.2. Eligible Treatment Facilities for Recommendation

ESKD patients often have mobility issues because of advanced age and poor health (Sakkas and Karatzaferi 2012). In our sample, patients travel, on average, 16.5 miles to their physicians. Most dialysis patients travel less than 10 miles for treatment (Prakash et al. 2014). Therefore, the need for a nearby treatment facility is a factor in physician recommendations. To illustrate, if a physician sees patients in Dallas, Texas, a dialysis treatment facility in Houston, Texas would not be included in the recommendation for his local patients. To reflect this preference for a local facility and lessen the computation burden, we define treatment facilities that are eligible for inclusion in the recommendation set as the 20 facilities closest to the physician as long as they are within a 70-mile radius. These criteria are chosen based on data analyses showing that approximately 94% of patients choose a facility among the 20 facilities closest to their physician's location. Additionally, less than 0.5% of patients are under the care of a physician more than 70 miles away.

Following Raval et al. (2016) and Kim and KC (2020b), we further define inside option facilities as those with at least 1% market share in each state per year, with the rest being outside options whose indirect utility is normalized to zero in the physician recommendation process. Our data show an 81% coverage of inside options.

4.3. Summary Statistics

Table 1 shows summary statistics of the sample of 16,978 first-time patients referred by 751 physicians in the United States. The data contain information on the referring physician only for patients with Medicare (i.e., patients older than 65 years old or with disability) prior

Table 1. Patient, Physician, and Facility Summary Statistics

Variable	Mean	Median	Standard deviation
Panel A: Patients			
Age (years)	70.4	72	11.5
Comorbidity index	5.9	6	2.8
Employed	0.86	1	0.34
Male	0.54	1	0.50
White	0.75	1	0.42
Black	0.21	0	0.40
Other races	0.03	0	0.18
Income ($1,000)	50.4	48.3	14.2
N	16,978	—	—
Panel B: Physicians			
Physician experience (years)	24.4	23	9.1
Physician affiliation	2.1	1.67	1.58
N	751	—	—
Panel C: Facilities			
Five-star rating	3.69	4	1.03
Dialysis adequacy (URR)	0.87	0.92	0.19
Anemia management (HGB)	0.50	0.52	0.15
Mortality	0.13	0.12	0.13
Chain status	0.92	1	0.27
N	1,356	—	—

Note. Quality measures are reported at the facility level based on averaging out across patients in each facility.

to dialysis treatment. For this reason, patients in our sample tend to be older, with a mean age of 70.4 years old. Our patient sample is 54% male, with the majority being white (75%). Physicians, on average, have 24.4 years of experience, including postgraduation training such as residency and fellowship. We also observe that physicians, on average, are affiliated with 2.1 treatment facilities.

Combining all patients' choice sets results in 1,356 inside-option dialysis treatment facilities nationwide. Panel C of Table 1 summarizes the characteristics of these treatment facilities. As can be seen, there is substantial variation among facilities in terms of five-star ratings (mean = 3.69, standard deviation = 1.03). To measure the dialysis quality more specifically, we also report the two dialysis-related service quality measures: dialysis adequacy (URR) and anemia management (HGB). The reported URR is at the facility level, which is based on the average yearly incidence of patients receiving an acceptable level of urea cleaning at any specific facility (urea cleaning is an indicator of how long a patient is connected to a dialysis station, and the CMS determines the acceptable level of the measure.). A URR greater than 65% is generally understood to be acceptable for dialysis patients. Therefore, we define an indicator for whether this value at the end of each dialysis claim is above this threshold or not. The statistics in panel C of Table 1 (e.g., URR of 0.87) can then be interpreted as the average proportion of patients' claims meeting the criteria of URR greater than 65% in a facility. Similarly, anemia management shows the average yearly incidence of managing patients' anemia at an acceptable level (mostly through injectable medications) across treatment facilities. Regarding HGB, 10 < HGB < 12 is the acceptable value, indicating enough anemia treatment dosage without the increased risk of cardiovascular diseases (Eliason et al. 2020). Therefore, we define an indicator variable of whether the HGB for each patient's claim is within this range and zero otherwise. As can be seen, treatment facilities, on average, perform a higher-quality job regarding urea cleaning compared with managing anemia. Regarding mortality, facilities report an annual average mortality rate of 0.13. Lastly, with regard to the ownership structure, we observe that the vast majority of treatment facilities in our sample are associated with large chains.

4.4. Reduced-Form Evidence

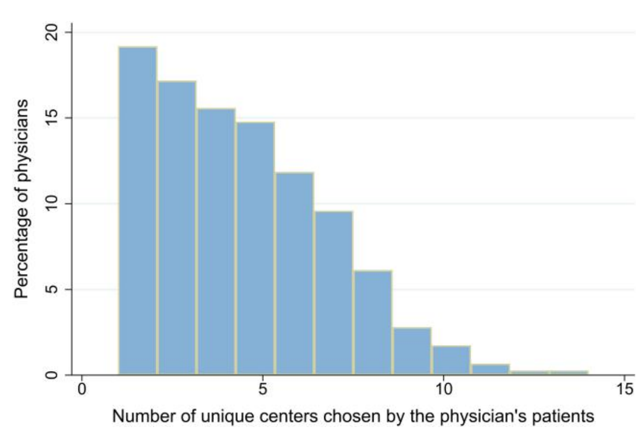
Our in-depth interviews with multiple kidney doctors revealed the importance of physician recommendations in patient choice of a treatment facility. Our interviews reveal that physicians might discuss with patients many factors, such as facility ratings, preferences for certain amenities (e.g., a big-screen TV for two- to three-hour dialysis sessions), and staff friendliness to some extent. This section offers reduced-form evidence of patient choice variation across physicians and the role of affiliation.

4.4.1. Patient Choice Variation Across Physicians. We first provide empirical evidence demonstrating that physicians may recommend diverse treatment facility sets as indicated by significant variations in the final choices made by patients across different physicians. More specifically, we consider the number of unique treatment facilities chosen by each physician's pool of patients. Figure 1 plots a histogram of the distribution of this variable across different physicians in our data.

Figure 1 shows a significant variation in the chosen pattern for different physicians; patients for approximately 7% of physicians have chosen one treatment facility, whereas patients for 3% of physicians have chosen from greater than or equal to 10 treatment facilities. This alludes to a substantial variance in recommendations across physicians. However, it is also possible that a portion of this variation can be attributed to the number of nearby treatment facilities around a physician. For example, patients living in a rural town with only two treatment facilities will end up choosing one of the two not because of their physician but because of the local availability of alternatives. Even after accounting for geographic differences, we still find substantial variation in the number of unique treatment facilities chosen across patients of different physicians (Online Appendix C). Taken together, the evidence points to the need to investigate and quantify how physician recommendations affect patients' choice of treatment facility, which we explore in this study.

4.4.2. Evidence of Conflicts of Interest. This study is also concerned with the expert's potential conflicts of interest in the form of a physician's affiliation with a treatment facility as the attending physician. We hypothesize that this affiliation affects patients' final

Figure 1. (Color online) Patients' Choice Pattern



Note. This plot shows the unique number of treatment facilities chosen by a given physician's patients.

choices by changing physicians' recommendation utility. More specifically, we run the following regression model to see if an affiliation is correlated with patient choice:

$$\Delta dist_{it} = \beta\, aff_{it} + \mathbf{X}_i\boldsymbol{\gamma} + \mathbf{d}_t + \epsilon_{it}.$$

Here, we define $\Delta dist_{it} = dist_{it}^{selected} - dist_{it}^{closest}$ as the difference in the distance between the treatment facility closest to patient i and the treatment facility that the patient chooses. Also, aff_{it} is defined as an indicator of whether the chosen treatment facility is affiliated with the patient's physician compared with the closest treatment facility that the patient chooses. Therefore, aff_{it} equals one if the patient's physician is affiliated with the selected treatment facility and not with the facility closest to the patient; otherwise, it is zero. Finally, $\mathbf{X}_i$ is a set of patient characteristics, such as age, race, gender, income, and comorbidity index, and $\mathbf{d}_t$ is a set of year fixed effects. In this equation, β can be interpreted as the marginal extra distance that patients are willing to travel for a treatment facility affiliated with their physicians relative to their closest nearby treatment facility after controlling for factors, such as the patient's characteristics.

Table 2 shows the result of this regression among patients who choose an inside option in their choice set, where we report the results without and with control variables in Model (1) and Model (2), respectively. Here, we find that β is significant and positive, suggesting patients' willingness to travel farther for treatment facilities that are affiliated with their physicians. Although this reduced-form analysis is correlational, the result implies that physician affiliation may play a role in affecting patient choice. We later investigate through the recommendation process how this affiliation, a potential conflict of interest, affects patients' choices and health outcomes.

5. Empirical Framework

In this section, we lay out the empirical framework that jointly models physician and patient behavior in a utility maximization framework. The starting point in the patient journey is the ESKD diagnosis. Based on this medical assessment, the physician usually recommends a set of treatment facilities to the patient. The patient then chooses her treatment facility based on her preference within the physician's recommendations. Given this process, our model is a two-stage model, where the first stage describes the recommendation process on the physician side and the second stage explains the final choice of patients given their physicians' recommendations.

Table 2. The Impact of Physicians' Affiliation on Patients' Choices

Variable	(1)	(2)
Affiliation	5.580***	5.597***
	(0.0311)	(0.0309)
Patient characteristics		✓
Year F.E.		✓
R^2	0.076	0.079
N	13,738	13,738

Notes. Standard errors are shown in parentheses and clustered at the treatment facility level. F.E., fixed effect.
***$p < 0.01$.

5.1. First Stage: Physician Recommendation

Interviews with physicians have revealed that they recommend a subset of the facilities depending on an individual patient's needs and preferences. Suppose there are J^k dialysis treatment facilities around physician k (up to 20 facilities as previously explained in Section 4.2). This section describes how the physician forms the recommendation set RS_i^k from J^k by defining physician utility (Sections 5.1.1–5.1.3) and costs (Section 5.1.5) that depend on various physician, patient, and treatment facility factors.

5.1.1. Physician Utility. We first define the physician k's recommendation utility of treatment facility $j \in J^k$ to patient i in the following equation:

$$u_{ij}^k = \mathbf{X}_{ij}^k \boldsymbol{\beta}_i + mv_{ij}^k. \tag{1}$$

Here, $\mathbf{X}_{ij}^k$ is a set of variables that allow recommendations to vary by the treatment facility's characteristics. First, it includes an affiliation indicator variable A_j^k that equals one if physician k is affiliated with treatment facility j and zero otherwise. This is the parameter of interest in the counterfactual analyses regarding the potential conflicts of interest via physician affiliation. Second, a chain indicator variable $chain_j$ equals one if the treatment facility j belongs to a large chain, such as DaVita or Fresenius, and zero otherwise. Third, it includes a distance variable $dist_{ij}$ representing the physician's consideration of the distance between the patient and the facility. Lastly, we add $dist_{ij}^2$ to account for the nonlinearity of the distance preference.

5.1.2. Patient Heterogeneity. Our model allows physicians to incorporate patient characteristics in the recommendation process by defining $\boldsymbol{\beta}_i$ in Equation (1) as the following:

$$\boldsymbol{\beta}_i = \bar{\beta}_0 + \mathbf{W}_i \boldsymbol{\beta}^o. \tag{2}$$

Here, $\bar{\beta}_0$ is the baseline parameter vector common across patients, and $\boldsymbol{\beta}^o$ is the set of parameters representing patient heterogeneity according to patients' characteristics. We include patient age, comorbidity index, gender, race, and income in the observed patients' characteristics in $\mathbf{W}_i$.

5.1.3. Match Value. In recommending treatment facilities to his patient, the physician may still have uncertainty about the fit of a treatment facility for his patient. To accommodate this uncertainty in the model, we include a "match value" denoted by mv_{ij}^k, which captures the fit between treatment facility j and patient i based on physician k's assessment. The physician is unaware of the exact match value mv_{ij}^k. However, his expert knowledge about the nearby treatment facilities enables him to have a noisy assessment of the match values. Following the literature (Mehta et al. 2003, Honka 2014, Beckert 2018), we assume that match values come from a type I extreme value (T1EV) distribution that provides mathematical tractability, where μ_{ij}^k is the location parameter and σ is the scale parameter:

$$mv_{ij}^k \sim T1EV(\mu_{ij}^k, \sigma). \tag{3}$$

We further define μ_{ij}^k as the following:

$$\mu_{ij}^k = \mathbf{H}_j\boldsymbol{\rho} + \tau\Gamma_j + \xi_{ij}^k, \qquad \xi_{ij}^k \sim \mathcal{N}(0, \omega_{jk}^2). \tag{4}$$

Here, $\mathbf{H}_j$ is a vector that contains vertical service quality measures—dialysis adequacy (URR_j), anemia management (HGB_j), and mortality ($MORT_j$). We should note that all of these quality measures are risk adjusted (see Online Appendix B for more details). In other words, we allow vertical quality measures to impact physicians' assessment of the fit of a treatment facility to their patients. These match values may also be affected by other factors, like concerns about capacity or crowdedness. We proxy it by constructing the utilization rate Γ_j, defined as the median split of the average ratio of the total number of dialyses performed to the number of patient beds available in facility j.

There can also be unobserved interactions between physicians and patients, such as discussions on various factors not captured in the data. These unobserved elements are represented by the term ξ_{ij}^k, which models the interaction between physician k and patient i for facility j as a normally distributed random variable with mean of zero and variance ω_{jk}^2, potentially affecting the physician's recommendation.

The term ω_{jk} represents the uncertainty level of physicians' private knowledge about various aspects of each center beyond the observed service quality measures (URR_j, HGB_j, and $MORT_j$) and the utilization rate (Γ_j). A larger ω_{jk} means that physician k has less precise private information about nearby centers (i.e., higher uncertainty). Therefore, it is natural to assume that ω_{jk} depends on a physician's familiarity with centers. For example, a physician who has been affiliated with a center for a longer time would have less uncertainty about the center. Our model accounts for this by parametrizing the standard deviation ω_{jk} as $\omega_{jk} = \omega_0 + \omega_1 fam_j^k$. The variable fam_j^k indicates whether an affiliated physician is highly familiar with the center based on the median split of the number of months that the physician is affiliated with the center.

Note that center-specific vertical quality measures ($\mathbf{H}_j$), utilization rate (Γ_j), and patient-level factors related to different facilities (ξ_{ij}^k) are assumed to be known to the physician, with the last one being unobserved to the researcher. However, there can be factors that are even unknown to the physicians themselves. For example, the physician may not have perfect information about how much each patient truly cares about things that they say or care about or how well the patient would get along with the staff or other patients at the treatment facility. Such residual uncertainty in evaluating match values in the market is captured by σ in Equation (3).

5.1.4. Recommendation—Benefits. Having established physician utility in making recommendations, we now discuss our operationalization of how physicians form their recommendations. Rearranging Equation (1), we can write physician utility as $u_{ij}^k \sim T1EV(\mathbf{X}_{ij}^k\boldsymbol{\beta}_i + \mu_{ij}^k, \sigma)$. Because the physician knows the match values up to a probabilistic distribution, he relies on the expected utility to recommend treatment facilities. Consider a subset S of J^k that physician k wants to recommend to patient i. Using the closed-form formula of the maximum statistics of T1EV distributions with the same scale parameter, we can write the physician's expected utility of recommending S as follows:

$$\mathbb{E}\left[\max_{j\in S}\left\{u_{ij}^k\right\}\right] = \frac{1}{\sigma}\log\left(\sum_{j\in S}\exp[\sigma(\mathbf{X}_{ij}^k\boldsymbol{\beta}_i + \mu_{ij}^k)]\right) + \frac{\gamma}{\sigma} \equiv I(S), \tag{5}$$

where γ is the Euler constant. We further denote Equation (5) as $I(S)$ for ease of notation, which can be interpreted as physician k's gross benefit of recommending $S \subseteq J^k$.

5.1.5. Recommendation—Costs. Interviews with physicians have revealed that new ESKD patients have very little prior knowledge about the dialysis process, let alone dialysis facilities. Therefore, explaining the specifics of all nearby treatment facilities J^k can be burdensome for the physician in a typical 20- to 30-minute patient visit. In other words, there is a cost associated with recommending more treatment facilities. Therefore, our model includes a cost to shape recommendations within a benefit-cost framework. The presence of a nonzero cost makes it likely for physicians to recommend a subset of nearby treatment facilities J^k rather than all of them. We define the physician k's cost for including facility j in the recommendation as follows:

$$c_{jk} = c_0 + \mathbf{F}_k\boldsymbol{\lambda} + \mathbf{F}_{jk}\boldsymbol{\pi}, \tag{6}$$

where c_0 is the average cost that is common across all physicians and centers. The term $\mathbf{F}_k$ is a set of physician factors that either facilitate or hinder the explanation process for specific physicians. We include physician experience ex_k (measured by years of medical experience) and busyness or workload $busy_k$ (measured by the number of patients seen in a quarter normalized by the busiest quarter for the physician relative to the busiest physician in the data).

There may also be other physician costs tied to recommending different centers, which we denote by $\mathbf{F}_{jk}$ in Equation (6). We consider two types of costs that are relevant to our context. First, the physicians' cost of recommendation may depend on the composition of nearby centers (e.g., how similar or dissimilar they are). We incorporate this by including a dissimilarity measure $dissimilar_{jk}$ to measure the dissimilarity of a center with the nearby centers around physician k based on Gower distance.[9]

Second, the five-star rating may have implications on the ease of including a center in the recommendation. For example, if a center has a high star rating, the physician might not need to justify including it in the recommendation set (i.e., lower cost). However, if the physician believes that a low-rated center could be a good match for a patient because of his private information, he might need to spend more time rationalizing recommending this center (i.e., higher cost). We include a dummy variable hs_j, indicating a high rating (defined as four stars or more) to account for this.

5.1.6. Recommendation Set Formation. We now outline how the optimal recommendation set is defined by combining the benefit (Section 5.1.4) and the cost (Section 5.1.5) of recommending a certain set of centers. Denoting the optimal recommendation set made by physician k for patient i as RS_i^k, we can write the physician's problem as the following:

$$RS_i^k = \underset{S \subset J^k}{\arg\max} \left\{ I(S) - \sum_{j \in S} c_{jk} \right\}. \tag{7}$$

This essentially posits that a physician solves the maximization problem in Equation (7) over all possible subsets of J^k that maximize the difference between the benefit of recommending a given subset S ($I(S)$) and its cost ($\sum_{j\in S} c_{jk}$). Note that this is a finite-set maximization problem, which results in the optimal recommendation RS_i^k. By substituting in Equation (5) and rearranging terms, the maximization problem can be rewritten as follows:

$$RS_i^k = \underset{S \subset J^k}{\arg\max} \left\{ \log\left(\sum_{j \in S} \exp(\sigma \hat{v}_{ij}^k) \right) - \sum_{j \in S} c'_{jk} \right\}, \tag{8}$$

where $\hat{v}_{ij}^k = \mathbf{X}_{ij}^k \boldsymbol{\beta}_i + \mu_{ij}^k$ and $c'_{jk} = c_{jk}\sigma$. This expression highlights that our empirical framework encompasses the characteristics of all available facilities, influencing both the size and composition of the recommendation set. The facilities' characteristics enter the benefit side through the $\log(\sum_{j\in S}\exp(\sigma\hat{v}_{ij}^k))$ term and the cost side through the $\sum_{j\in S} c'_{jk}$ term. Comparing the balance between these two components across all possible subsets of J^k determines the composition and size of the optimal physician recommendation set simultaneously.[10]

5.2. Second Stage: Patient Choice

Having the recommendation from the physician, the patient now chooses a facility that maximizes her utility in the second stage. We define patient i's utility in choosing a dialysis treatment facility j among the recommendation RS_i^k as the following:

$$U_{ij} = \mathbf{E_{ij}} \boldsymbol{\eta}_i + \epsilon_{ij}. \tag{9}$$

Here, $\mathbf{E_{ij}}$ is a set of variables that enter patient utility as follows. Similar to other healthcare markets, research shows that distance plays an important role in the dialysis market (Velázquez et al. 2022). This is not surprising given that these patients need to visit the treatment facility three times weekly. Thus, we include linear and quadratic distance measures in the patient utility ($dist_{ij}$ and $dist_{ij}^2$). In order to capture any patient preference for chain treatment facilities, we include a dummy variable indicating chain status $chain_j$ in the utility. We also include each facility's CMS five-star rating, which simplifies quality measures into a single metric for patients and is readily accessible on the CMS website.

Lastly, we include the ranking of each facility in the recommendation, implied by physician's utility $\hat{v}_{ij}^k$ in Equation (8). Although we do not directly observe whether physicians rank the facilities when presenting the recommendations to the patients or what the ranking is, our empirical framework allows for such a possibility by including the inferred ranking in patient utility.

We also account for patients' heterogeneous tastes regarding variables in their utility function by interacting all of the variables with the set of previously introduced patient characteristics $\mathbf{W}_i$ in Equation (2):

$$\boldsymbol{\eta}_i = \bar{\eta}_0 + \mathbf{W}_i \boldsymbol{\eta}^o, \tag{10}$$

where $\bar{\eta}_0$ is the baseline parameters common across patients and $\boldsymbol{\eta}_o$ is the set of parameters representing patient heterogeneity according to patients' characteristics.

Assuming that the error term ϵ_{ij} in Equation (9) follows a standard T1EV distribution, the conditional probability of choosing treatment facility j given the optimal recommendation set RS_i^k can be written as the following:

$$\text{Prob}\,(j \mid RS_i^k) = \begin{cases} \dfrac{\exp(V_{ij})}{\sum_{l \in RS_i^k} \exp(V_{il})} & \text{if } j \in RS_i^k \\ 0 & \text{otherwise,} \end{cases} \tag{11}$$

where $V_{ij} \equiv \mathbf{E_{ij}} \boldsymbol{\eta}_i$ denotes the observed part of the patient utility in Equation (9).

As Equation (11) suggests, physicians' preferences can sway patients' choices in two key ways when patients make decisions about their treatment facilities. First, the physician's preferences can affect which facilities are recommended to the patient. Second, the physician's evaluations can influence the order in which these options are presented to the patient.

5.3. Identification

In this section, we discuss the identification of the parameters in the estimation process.

5.3.1. Exclusion Restrictions and Selection. In the two-stage model, the likelihood function can be decomposed into two parts: (a) the part that accounts for the physician's recommendation stage and (b) the other part that captures the patient's selection process given the unobserved recommendations to the econometrician. Therefore, we need exclusion restrictions to identify parameters in the two stages separately, which shift one stage without affecting the other (e.g., Gaynor et al. 2016, Beckert 2018, Crawford et al. 2021).

In our framework, exclusion restrictions stem from two factors that are assumed to influence physician utility only: physician affiliation A_j^k and risk-adjusted quality metrics $\mathbf{H}_j$. We assume that physician affiliation affects only physician recommendations but not patient decisions for two reasons. First, affiliation information is not publicly available. We obtained it by requesting data from the USRDS and combining them, but it would be difficult for patients to access such information. Second, the opaqueness of physician affiliations is underscored by the 2022 California Proposition 29, which mandated the disclosure of physician affiliations with dialysis centers to patients. Although it did not pass, its inclusion on the ballot underscores the prevalence of nondisclosure at the population level, thereby supporting our exclusion restriction assumption regarding affiliation.

We posit that risk-adjusted quality measures (URR, HGB, and mortality) affect physician recommendations but not patient decisions for three reasons. First, interviews with physicians indicated that patients, who are predominantly elderly with a median age of 72 years old, generally lack awareness of these complex metrics that require medical expertise for interpretation. Second, this assumption is in line with the literature on healthcare markets (e.g., Beckert 2018). Third, the U.S. Government's investment in providing center-quality information via nontechnical, easy-to-understand five-star ratings underscores the existing obstacles that patients face in accessing such information. The CMS states that the purpose of the five-star ratings is to "make quality information easy to access and understand for consumers," suggesting information friction among the average patients regarding the complex quality measures. Therefore, we assume that patients are unlikely to consider complex risk-adjusted quality measures at the population level.

In addition to exclusion restrictions, there can also be a concern about selection bias: Patients may select nephrologists based on their affiliations with specific dialysis centers. However, interviews with nephrologists indicate that such selection is unlikely as patients with kidney disease are typically referred to nephrologists before the necessity for dialysis becomes apparent. Dialysis, a last-resort treatment for kidney disease, is not required for all patients. Conditions such as hypertension can progressively damage the kidneys, especially when combined with other disorders, like diabetes, increasing the likelihood of progressing to severe kidney disease that necessitates dialysis. Given the unpredictable progression of kidney disease and the potential future need for dialysis, patients are unlikely to choose a nephrologist based on dialysis center affiliations at the time of initial diagnosis, especially when such information is not readily available.

5.3.2. Parameter Identification. The identification of patient utility parameters is straightforward as it is described in the choice model literature; they can be identified because of variations in the individual choice patterns corresponding to different treatment facilities' characteristics in the patient choice set and patients' characteristics. Similarly, $\boldsymbol{\beta}_i$ in Equation (1) and $\boldsymbol{\rho}$ and τ in Equation (4) can also be identified because of variations in recommendation patterns corresponding to variations in treatment facilities' characteristics.

The identification of physicians' uncertainty of private information (ω_{jk} in Equation (4)) hinges on data variations in frequency distributions of chosen treatment facilities among similar nearby patients referred by comparable physicians. Put differently, similar patients consulting similar physicians should result in similar recommendations and choices. Within a similar set of patient-physician pairs, we can attribute the variation in frequency distributions of the chosen treatment facilities to the variance of unobserved private information ω_{jk}^2.

The identification of the match value scale σ comes from the fact that the function $I(RS_i^k)$ in Equation (5) is decreasing with respect to σ, and hence, recommendations are becoming smaller as σ increases (Mehta et al. 2003). Therefore, as Beckert (2018) points out, the parameter is identified through the variation in recommendation set sizes across physicians with similar levels of cost.

5.3.3. Monte Carlo Simulation. To bolster our argument regarding identification, we conduct a Monte

Carlo simulation to demonstrate the model's capability to recover parameters accurately. More specifically, we choose a sample of 1,500 patients in our data and select a set of true parameters. We then simulate their facility choices given the true parameters and run our estimation based on the simulated choices. Tables A.2 and A.3 in Online Appendix D reveal close proximity between true and estimated parameters, reinforcing our confidence in parameter identification.

Moreover, beyond the parameter recovery, we evaluate the model's performance in recovering recommendations. Leveraging the simulation data, where true physician recommendations are assumed to be known, we statistically assess our model's ability to recover unobservable recommendations based on the exclusion restriction arguments and model primitives. Comparing the estimated recommendations with true ones, we find perfect recovery in 73.24% of the draws, with differences of no more than one center in 95.9% of draws. This underscores the model's capability to recover recommendations to a reasonable extent.

In summary, the Monte Carlo simulation demonstrates the empirical framework's ability to successfully recover parameters and recommendations, even when facing unobserved recommendations.

5.4. Estimation Procedure

Because there is no closed-form solution for the physician recommendation in Equation (8), we use simulated maximum likelihood. For each physician k, patient i, and nearby treatment facility j, we take D draws of unobserved match value ξ_{ij}^k from $\mathcal{N}(0, \omega_{jk}^2)$ in Equation (4). We then write the probability of the recommendation stage as an indicator function that determines whether treatment facility j is part of the recommendation for each draw. The probability of patient i choosing facility j can then be expressed as the following:

$$Prob(i \to j) = \frac{1}{D}\sum_{d=1}^{D} \mathbb{1}(j \in RS_i^k(d)) Prob(j \mid RS_i^k(d)), \tag{12}$$

where $RS_i^k(d)$ is the recommendation set made by physician k for patient i given draw d following Equation (8). We can then write the likelihood function as the following:

$$L = \prod_{i=1}^{N} \prod_{j} [Prob(i \to j)]^{1(i \to j)}. \tag{13}$$

Because of the fact that an indicator function represents the recommendation process in Equation (12), the likelihood function contains discontinuities. We address this issue using a kernel smoothing method. We further provide the details along with a numerical example in Online Appendix E.

6. Estimation Results

In this section, we provide the estimation results of the structural model along with a discussion of the key findings. Following Gaynor et al. (2016) and Kim and KC (2020b), we convert our continuous variables to indicator variables based on the median for ease of interpretation. For example, a physician is considered highly experienced (i.e., $ex_k = 1$) if the number of years of experience is higher than the median of all physicians in the data (and $ex_k = 0$ otherwise). We first present results from the physician recommendation stage followed by those for patient utility. Because of space constraints, this section focuses on the main effects, briefly discussing heterogeneity. We present the complete parameter estimates, including all interaction terms, in Online Appendix F. Before presenting the estimation results and for the ease of tracking different model components, we summarize parameters used in the model specification in Table 3.

6.1. Physician Recommendation Parameters

Table 4 presents parameter estimates in the physician recommendation stage. First, physician affiliation with a treatment facility is positive and statistically significant (5.828, $p < 0.01$). This indicates that, on average, physicians are more likely to recommend a treatment facility with which they are affiliated. Second, physicians tend to recommend their patients to nearby centers (-1.384, $p < 0.01$), reflecting the patients' preference for shorter travels for more than 140 dialysis sessions per year. The positive quadratic distance estimate (0.093, $p < 0.01$) indicates that the marginal disutility of distance decreases as distance increases. We also observe that physicians' preference for distance is heterogeneous. For example, they prefer to recommend older patients to even closer facilities (-0.064, $p < 0.01$)

Table 3. Description of Parameters

Notation	Description
$\bar{\beta}_0$	Baseline parameter for patient heterogeneity in recommendation
$\boldsymbol{\beta}^o$	Parameters for patient heterogeneity in recommendation
μ_{ij}^k	Location parameter of match value
σ	Match value scale
$\boldsymbol{\rho}$	Coefficients related to risk-adjusted quality metrics
τ	Coefficient related to utilization rate
ξ_{ij}^k	Unobserved component of match values
ω_{jk}	Variance of physician's private knowledge
ω_0	Intercept of variance of physician's private knowledge
ω_1	Physician familiarity coefficient
$\boldsymbol{\lambda}$	Coefficients related to physician cost at physician level
$\boldsymbol{\pi}$	Coefficients related to physician cost at the facility level
$\bar{\eta}_0$	Baseline parameter for patient heterogeneity in patient utility
$\boldsymbol{\eta}^o$	Parameters for patient heterogeneity in patient utility

Table 4. Physician Recommendation Parameter Estimates

Group	Variables	Parameter estimates
Physician utility	*Affiliation*	5.828*** (0.019)
	Chain	−0.388*** (0.027)
	Distance	−1.384*** (0.009)
	Distance^2	0.093*** (0.002)
Match value	*Dialysis adequacy*	0.164*** (0.005)
	Anemia management	0.246*** (0.012)
	Mortality	−0.158*** (0.007)
	Intercept of variance of private information	−0.359*** (0.013)
	Familiarity	−0.731*** (0.007)
	Match value scale	−0.954*** (0.009)
	Utilization rate	0.126*** (0.009)
Physician cost	*Cost intercept*	−3.207*** (0.016)
	High experience	−0.018 (0.013)
	Busy	−0.150*** (0.012)
	Dissimilarity	−0.871*** (0.007)
	High star rating	−0.040** (0.017)

Notes. We report the log transformation log(.) for the match value scale. Standard errors are shown in parentheses. We used $D = 50$ and $\kappa = 10$ for the estimation.
$^{**}p < 0.05$; $^{***}p < 0.01$.

as they are more likely to have mobility issues (see Online Appendix F).

Table 4 also presents the parameter estimates of the match value components in Equation (4), which are all statistically significant at the 5% significance level. We first consider parameter estimates of the observed mean components ($\mathbf{H}_j$). In line with expectations, we find that physicians prefer to include facilities with better dialysis adequacy (URR), better anemia management (HGB), and lower mortality in their recommendations. Our estimation shows that utilization rate positively influences physician recommendations (0.126, $p < 0.01$), suggesting that physicians favor recommending facilities with higher utilization rates. This implies that higher utilization rates are indicative of higher unobserved qualities, such as operational efficiency in managing larger patient volumes, rather than reflecting capacity constraints, like crowdedness.

For the unobserved mean component of the match values (ξ_{ij}^k), we apply an exponential function to ω_{jk} to ensure a nonnegative value. We find that a physician's private knowledge about less familiar dialysis centers has a standard deviation of $\exp(-0.359) = 0.698$. However, the standard deviation decreases for centers with which they are more familiar ($\exp(-0.359 - 0.731) = 0.336$). These findings align with the expectation that physicians have less uncertainty about centers where they have extensive experience. Lastly, applying a similar exponential transformation, we determine that the scale parameter of the physicians' match value distribution (σ) is $\exp(-0.954) = 0.385$, indicating general uncertainty about the match between patients and dialysis centers in the dialysis market.

Regarding the physician cost parameter estimates, we again apply an exponential function to the cost components in Equation (6) to ensure a nonnegative cost function. With respect to physician characteristics ($\mathbf{F}_k$), our analysis reveals no significant difference in physician experience (ex_k) in relation to the explanation cost. On the other hand, we find that physicians with high workloads ($busy_k$) tend to have a lower explanation cost (-0.150, $p < 0.01$), indicating increased efficiency in handling a high patient volume.

With respect to heterogeneous cost effect across facilities ($\mathbf{F}_{jk}$), we find that if a center is different than other nearby centers (higher dissimilarity), it is easier for the physician to recommend that center (-0.871, $p < 0.01$). This result is consistent with contrast bias, a cognitive phenomenon wherein individuals find it easier to make decisions among options that are distinctly different, as evidenced by Tversky and Kahneman (1974) and Simonson and Drolet (2004).

Lastly, we observe that the physician cost of including centers with higher star ratings ($hs_j = 1$) in the recommendation is smaller. In other words, if a center has a high star rating, then the physician may not need to justify including it in the recommendation set (i.e., lower cost).

Overall, our model predicts that physicians recommend an average of 5.44 treatment facilities to their patients. In 31.3% of these instances, they recommend only the centers with which they are affiliated. Although this may indicate potential conflicts of interest, further investigation is necessary to understand how these affiliations influence patient health outcomes through physician recommendations. We address it with counterfactual analyses in Section 7.

6.2. Patient Utility Parameters

We report the estimation results for patient utility in Table 5. Similar to the physician stage, we suppress

Table 5. Patient Utility Parameter Estimates

Variable	Estimates
Distance	−1.194*** (0.014)
Distance^2	0.075*** (0.003)
Five-star rating	0.115*** (0.006)
Chain	1.095*** (0.009)
Ranking	−2.773*** (0.010)
Log likelihood	−17,609.462
AIC	35,344.923
BIC	35,832.523

Notes. Standard errors are shown in parentheses. AIC, Akaike information criterion; BIC, Bayesian information criterion.
***$p < 0.01$.

interaction term estimates in this section for brevity and instead, present them in Online Appendix F. First, as expected, patients dislike traveling far for regular dialysis (−1.194, $p < 0.01$). In addition, the marginal disutility of distance decreases, similar to the case of physicians. Second, patients prefer higher star ratings when choosing a treatment facility (0.115, $p < 0.01$), suggesting that patients respond to the government program aimed at providing them with more information on treatment facilities through the five-star rating website. Additionally, we observe heterogeneous patient responses to the star ratings. Specifically, sicker patients are more likely to respond to the quality information (0.115, $p < 0.01$), possibly because of the higher risks of choosing an inferior facility. On the other hand, African American patients in lower-income areas tend to respond less to the ratings. This asymmetric response across socioeconomic factors suggests that access to and familiarity with online health resources among disadvantaged groups may influence their use of star ratings, despite government mandates to provide such quality information in the market. Third, we observe a general preference for large dialysis chains among patients. Lastly, our findings indicate that centers ranked more favorably by physicians (lower inferred ranking $rank_{ij}$) are more likely to be chosen by patients (−2.773, $p < 0.01$). This implies that patients may be adept at evaluating the relative importance of different centers in a ranked recommendation list.

6.3. Comparison Against the Single-Stage Model

So far, we have assumed that the choice of a treatment facility follows a two-stage process, mirroring real-world scenarios where physicians recommend a set of centers to patients who then decide. This framework is corroborated by insights from nephrologist interviews. Alternatively, one could assume that physicians assess all patient needs and choose the best center for the patients in a single-stage framework without recommendations.

This section compares our framework against such an alternative by first developing a single-stage utility framework, combining all relevant variables, like affiliation, distance, chain status, and quality measures, while incorporating patient heterogeneity similar to the two-stage model. Assuming a type I extreme value distribution for the error term, the physician assesses all nearby centers and selects the optimal one for the patient. Note that certain variables crucial to the two-stage model, such as physicians' private information, the match value scale, and physician explanation cost, are omitted in the single-stage framework as the recommendation process is removed. Tables A.8 and A.9 in Online Appendix F present the results.

Results in Tables A.8 and A.9 in Online Appendix F indicate two issues with the single-stage model. First, the single-stage model provides a worse statistical model fit compared with the two-stage model. Tables 5 and A.9 in Online Appendix F show that the two-stage model has a substantially lower AIC, 259 points less than the single-stage model, as well as lower BIC by a factor of 27 units. It is worth noting that when the AIC or BIC difference exceeds 10, it suggests strong evidence in favor of the model with the lower AIC and BIC (Kass and Raftery 1995, Claeskens and Hjort 2008).

Second, beyond the model fit, the single-stage model produces results that do not conform with the conventional wisdom of physician behavior in the market. Specifically, results suggest that physicians/patients prefer treatment facilities with significantly worse dialysis adequacy (−0.391, $p < 0.01$), worse anemia management (−0.349, $p < 0.01$), and higher mortality (0.422, $p < 0.01$). These somewhat unexpected results can be explained by comparing the quality metrics of recommended and nonrecommended facilities. Recommended facilities exhibit lower-quality metrics, with an average URR decrease of 0.012, an HGB decrease of 0.006, and a mortality increase of 0.002, all statistically significant at the 1% level. Additionally, an analysis of raw data comparing chosen and nonchosen facilities—including all nearby centers and not just those in recommendation sets—reveals that patients select lower-quality (below-median) facilities in 85.5% of cases. These data patterns explain the negative signs for quality metrics in the single-stage model.

Although the single-stage model assumes that physicians and patients share full information, this lacks face validity. Patients often have limited information, especially when choosing unfamiliar services, like dialysis. Moreover, their preferences may differ from those of physicians, prioritizing factors like distance and star ratings over quality, an observation supported by physician interviews. Unlike the single-stage model, our two-stage model flexibly allows for a limited information decision process and different preferences of physicians and patients. For example, our two-stage model allows a patient's distance sensitivity to be different from that of a physician.

This essentially goes back to the role of taking into account consideration sets in empirical search problems. This issue has been shown in several different contexts in the literature and solved by using two-stage models to address different preferences at the consideration/recommendation stage and choice stage (Bronnenberg and Vanhonacker 1996, Goeree 2008, Ching et al. 2009, Terui et al. 2011). As noted by Honka et al. (2019, p. 204), "When consumers have limited information, i.e., only consider a subset of all available products for purchase, and this limited information is not accounted for in the model and estimation, it will lead to biased preference estimates."

Therefore, we believe that the sign reversal stems from the fact that the two-stage model accounts for the consumer's limited information. To test this explanation, we estimated an alternative reduced-form two-stage model without imposing our structural specification on how the recommendation list is generated. Specifically, we employ a simple two-stage logit specification inspired by Gaynor et al. (2016), where consideration sets are formed based on utilities exceeding a threshold. Results of this reduced-form two-stage model——unaffected by the limited information bias present in the single-stage model——are reported in Tables A.10–A.13 in Online Appendix G. As expected, these results align with our main model, confirming physicians' preference for higher-quality facilities. Specifically, the model indicates a preference for higher-quality facilities by physicians: positive preferences for dialysis adequacy (0.068) and anemia management (0.074) and a negative preference for mortality (−0.061), all statistically significant at the 5% level. These findings suggest that the sign reversal in the single-stage model likely results from its failure to separate the recommendation and choice stages, a distinction explicitly accounted for in our two-stage model.[11]

In summary, our two-stage model, which distinguishes recommendations (first stage) and patient choices (second stage), offers more realistic results with a superior data fit. These results underscore the importance of taking into account expert recommendations using a two-stage framework to address consumers' limited information.

7. Policy Simulation

The estimation results on both the physician recommendation process and patient demand allow us to evaluate the impact of important policies in this market. This section presents the results of relevant policy simulations on patient choice of treatment facility and patient health outcomes.

7.1. Policy Simulation Overview

Our policy simulations are motivated by two issues that have garnered substantial interest in the kidney care industry and the overall healthcare sector—information provision and conflicts of interest. First, we consider the case of improved information provision in this market. With the rise of consumerism in U.S. healthcare, consumer advocates have called for improved information provision in medical settings (Oshima Lee and Emanuel 2013). For example, Section 3506 of the ACA explicitly encourages a better flow of information in the market to promote medical care that better matches patients' preferences. Given the uncommon but critical nature of ESKD, information provision is particularly relevant in kidney care. To improve the availability of information to all stakeholders in the market, the CMS introduced the five-star rating program for dialysis centers in 2015. This government initiative is designed to "make quality information easy to access and understand for consumers," thereby helping them "have a better understanding of the care they receive."[12] We assess the value of this information provision effort by conducting counterfactual analyses without the rating data using two approaches: first, allowing the market to form expectations when five-star ratings are unavailable[13] and second, removing the rating entirely from the model.

Second, we investigate the issue of conflicts of interest in the healthcare setting. The increasing trend in physician affiliations with care facilities, a potential conflict of interest, has raised concerns over consumer protection and patient welfare because it may skew the physician recommendations given to patients in a way that may not be in their best interest (Brennan et al. 2006, Guo et al. 2021). This issue has raised significant concerns in the kidney care market, leading to efforts to address it. For instance, California Proposition 29, which appeared on the ballot during the 2022 midterm elections, sought to mandate the disclosure of substantial financial relationships between a referring physician and a potential treatment facility to patients. Because of the optics of conflicts of interest, this requirement would have made it more difficult for physicians to recommend centers with which they are affiliated. Although it did not pass, this highlights the public interest in and scrutiny of physician affiliations with treatment facilities. We explore this issue by conducting a counterfactual scenario in which using affiliation as a basis for recommendation is prohibited. This counterfactual is further motivated by our interview with a physician at a major teaching hospital in the U.S. Southwest who revealed that their hospital avoids recommending their own treatment facility because of the potential appearance of a conflict of interest.

Both of these policies—information provision and conflict of interest—impact physician recommendations, which subsequently change the patients' choices in the market.[14] Our structural model provides a basis for investigating these policies by considering both physician and patient decision making in this market. A key objective in assessing the effectiveness of a healthcare policy change is to evaluate its potential impact on patient health outcomes. Accordingly, we assess patient welfare and quality of care using mortality rates, which are notably high for our focal patients—about 15% annually. Putting this number in perspective, coronary artery disease, the most common type of heart disease, has an annual mortality rate of around 2%.[15]

7.2. Mortality Estimation

The aforementioned policies change physician recommendations, which can affect patient treatment facility choices and subsequently, the patient outcome in terms of mortality. To quantify the effect of policy changes on mortality in counterfactuals, we need to model risk-adjusted patient mortality attributed to each treatment facility. Specifically, we use the following model:

$$mor_{ijt} = \mathbf{X}_i\boldsymbol{\gamma} + \mathbf{d}_t + \mathbf{D}_j + \epsilon_{ijt}, \tag{14}$$

where mor_{ijt} is an indicator function that equals one if the patient i dies in time t while being treated at treatment facility j and zero otherwise. Vector $\mathbf{X}_i$ is a set of patient i's risk factors that could impact mortality, such as age or comorbidity index; vector $\mathbf{d}_t$ is a set of year fixed effects; and $\mathbf{D}_j$ is treatment facility fixed effects. In this setting, $\mathbf{D}_j$ can be interpreted as the portion of mortality that can be attributed to the treatment facility beyond patient-specific or time-specific factors. Therefore, as policy changes alter patient choice probabilities, their impact is measured by the difference in expected mortality of the patient before and after a policy change. Similar approaches have been used to study patient health outcomes in Gowrisankaran and Town (1999), Gaynor et al. (2016), and Kim and KC (2020b).

Gowrisankaran and Town (1999) point out that mortality can be attributed to unobserved factors to the researcher that might correlate with the choice of the healthcare facility. Thus, it is common for a patient or her physician to consider unobserved factors when deciding which treatment facility the patient should choose. Therefore, a simple estimation of $\mathbf{D}_j$ using Equation (14) is likely to be biased because of this selection issue. To obtain unbiased estimates of $\mathbf{D}_j$, we use two approaches: using IVs to correct the endogeneity issue and employing a machine learning technique to improve the precision of the estimates.

7.2.1. Instrumental Variables to Address Selection Bias.

Consistent with previous literature (Gowrisankaran and Town 1999, Gaynor et al. 2016, Kim and KC 2020b), we use distance IVs based on the distance between patients' residences and nearby treatment facilities using centroids of zip codes. This is relevant because the distance is negatively correlated with the choice of the facility as patients receive the disutility to travel far for dialysis. The exclusion restriction is then based on the assumption that the unobserved severity of illness beyond control variables is identically distributed in the population. We use three instrumental variables: the distance and the squared distance between the patient and the treatment facility and the indicator function for the closest treatment facility.

7.2.2. Machine Learning to Improve Precision.

Estimating standard linear instrumental variable models, such as two-stage least squares (2SLS), has drawbacks because it results in the loss of some instrumental variations. This, in turn, can lead to a loss of precision in estimating the outcome of the first stage of 2SLS and even bias estimates in some cases. To mitigate these issues and capture nonlinearity patterns among covariates, we use machine learning techniques in the first stage of 2SLS, which allows us to easily handle high-dimensional data and improve prediction performance (see Chen et al. 2021 for details). This high-dimensionality issue is especially important in our research setting. A hospital typically serves many patients in need of mostly one-time treatments, such as surgeries, whereas a dialysis center operates differently and is based on serving a small number of patients more than 140 times per year. Therefore, our setting contains many treatment facilities compared with the number of patients; having more than 1,350 treatment facilities with three instrumental variables results in more than 4,000 variables, where we use machine learning to deal with high-dimensionality issues.

More specifically, in the first stage, we need to predict the choice of treatment facility for each patient based on the variety of individual risk factors and location measure IVs. This translates into $\mathbf{D}_j = f(\mathbf{X}_i, \mathbf{d}_t, \overrightarrow{\mathbf{IV}}_j)$, where $\overrightarrow{\mathbf{IV}}_j$ denotes the vector of the instrumental variables and $f(\cdot)$ represents the machine learning-based functional form that takes into account a more flexible relationship between risk factors and patient locations on patient treatment facility choices. Because the dependent variable here is whether a patient selects the treatment facility j, this amounts to a classification problem, where we take advantage of deep ANNs.

Deep neural networks are particularly a suitable choice as they are designed to explore hidden layers and flexible relationships between exogenous factors and instrumental variables. We feed the probability of these predictions $(\hat{\mathbf{D}}_j)$ to the second stage of 2SLS, where we regress Equation (14) with the predictions replacing the endogenous variable $\mathbf{D}_j$. We should note that this method would be invalid if the prediction power of the first stage is so high that it perfectly recovers the endogenous choices. This is not the case in our study. Even an ANN with 10 deep layers, which has even been tuned using Bayesian optimization, is only 59% accurate in predicting the endogenous choice $\mathbf{D}_j$. We provide details on the implementation of ANN and the associated use of the Bayesian optimization technique in Online Appendix H.

7.2.3. Incorporating Uncertainty into Mortality. Although our model estimates the coefficient representing unbiased mortality rates at different centers ($\hat{\mathbf{D}}_j$ in Equation (14)), it is important to acknowledge that this is an estimated value with substantial uncertainty. To account for such uncertainty in our evaluation of counterfactual policies, we go beyond just relying on the estimated mean coefficient $\hat{\mathbf{D}}_j$. Instead, we take random draws for each treatment facility j from the estimated normal distribution of $\hat{\mathbf{D}}_j$, calculate the counterfactual health outcomes, and report the effect of the policy simulation on mortality. We provide further discussion on this issue in Online Appendix I.

7.3. Policy Simulation Results

Table 6 provides policy simulation results for the previously proposed two policy simulations: (CF1) absence of information provision regarding the CMS five-star ratings and (CF2) recommendation without physician affiliation—a potential source of conflicts of interest.

7.3.1. Information Provision. First, we assess the value of the CMS's five-star ratings in the market. As discussed previously, the CMS's five-star rating is a government initiative to make dialysis center quality information available to stakeholders in the market. We evaluate the impact of this information by examining a counterfactual scenario without five-star ratings. In scenario I, we rely on market expectations to estimate the unavailable ratings. In scenario II, we "turn off" the ratings, removing this quality information from physician recommendations and patient choices.

Table 6 demonstrates that without the five-star ratings, the average mortality would rise by 0.03%–0.15% depending on model specifications. The left panel of Figure 2 plots the distribution of the mortality change over simulation draws, illustrating a consistent trend toward increased mortality. Back-of-the-envelope calculations show that without the five-star ratings, there would have been approximately 16–76 additional kidney patient deaths annually (95% CIs = [6, 26] and [56, 96], respectively) depending on model specifications.[16] This finding demonstrates the concrete benefits of providing quality information in the market, reinforcing the broader trend toward increasing information availability and transparency in the healthcare market.

7.3.2. Recommendation Without Potential Conflicts of Interest. In the second policy evaluation, we focus on the case of conflicts of interest in the recommendation process by considering physician affiliation with a facility as its proxy. To study ways to manage potential conflicts of interest, we evaluate the effect of a ban on the usage of physician affiliation as a basis for their recommendations. This is done by effectively shutting down the effect of A_j^k in physician utility.

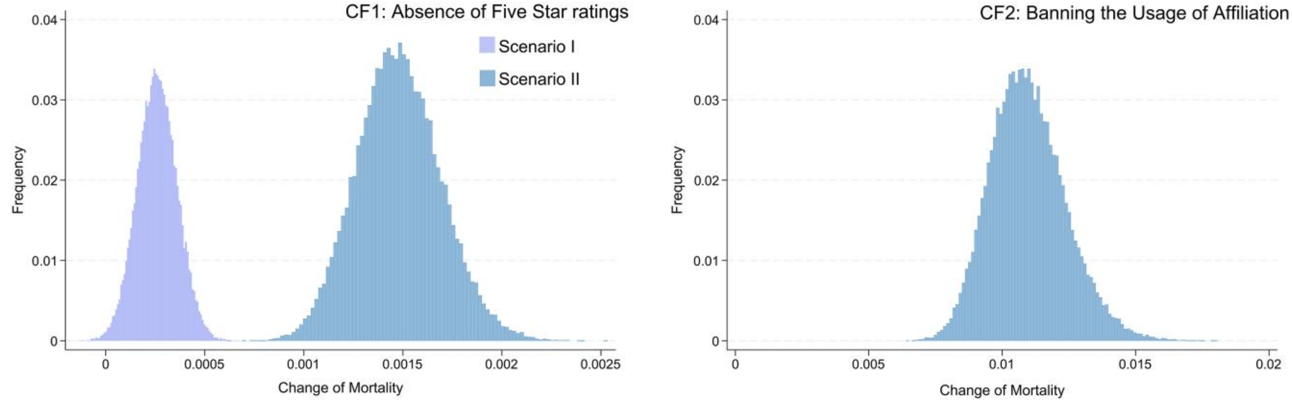
Our counterfactual results show that this policy increases mortality by 1.1% from the current 14.3%–15.4%.[17] The right panel of Figure 2 shows the distribution

Table 6. The Impact of Proposed Policies

Related counterfactual	Mortality
CF1: Absence of five-star ratings	
Scenario I: Expectation-level ratings	
Baseline mortality	0.143
Normalized mortality change (counterfactual − model prediction)	0.0003
95% Confidence interval of mortality change	[0.0001, 0.0005]
Overall mortality change direction	Increase
Scenario II: No ratings	
Baseline mortality	0.143
Normalized mortality change (counterfactual − model prediction)	0.0015
95% Confidence interval of mortality change	[0.0011, 0.0019]
Overall mortality change direction	Increase
CF2: Banning the usage of affiliation	
Baseline mortality	0.143
Normalized mortality change (counterfactual − model prediction)	0.011
95% Confidence interval of mortality change	[0.008, 0.014]
Overall mortality change direction	Increase

Notes. We use $B = 50{,}000$ draws for each facility to approximate the distribution of mortality estimates and calculate the confidence intervals. In scenario I, the market uses expected ratings when five-star ratings are unavailable, whereas in scenario II, ratings are turned off in the model.

Figure 2. (Color online) Impact of the Absence of Five-Star Ratings (Left Panel) and the Ban on Conflict of Interest (Right Panel) on Mortality Changes



Note. In the left panel, from left to right, we report the impact of the absence of information provision under the case of expectation-level rating (scenario I) and the case of no rating at all (scenario II), respectively.

of changes in mortality. Consistent with the earlier counterfactual analysis, the positive values of the distribution indicate an increase in mortality. Similar back-of-the-envelope calculations show that recommendations without affiliation as a basis would result in 553 additional kidney patient deaths annually (95% CI = [402, 703]). This result suggests that a ban on the usage of physician affiliation in recommendations would hurt patient health outcomes.

To put it differently, this empirical result does not support the notion that physician affiliation, a potential source of conflicts of interest, always hurts consumers or patients. One possible mechanism that can explain this phenomenon is through the lens of dialysis quality. One might expect physicians to be interested in being affiliated with higher-quality treatment facilities for financial reasons tied to Medicare's pay for performance and general reputation. If this is the case, an outright ban on the use of affiliation might result in patients being recommended to lower-quality treatment facilities, resulting in worse patient outcomes in terms of mortality.

To investigate this mechanism, we check to see if treatment facilities with high levels of affiliations tend to have higher dialysis quality. We use a regression analysis, where the dependent variable is the dialysis quality (dialysis adequacy, anemia management, and mortality measures) and the independent variable is whether the treatment facility is highly affiliated based on the number of physician affiliations. The results indicate that facilities with more affiliations are more likely to be of higher quality,[18] which can explain why an outright ban on physicians' conflicts of interest may hurt patients. Although we do not find a negative impact of conflict of interest on patients, our results should be viewed with caution. We consider the conflict of interest only through the affiliation of a physician with a treatment facility. It is possible that conflicts of interest may manifest in ways other than affiliation that do not benefit patients.

To ensure the robustness of our counterfactual analyses, we conducted comprehensive sensitivity analyses by systematically perturbing the recovered physician recommendations across size, composition, and type of perturbation. Detailed results in Online Appendix J (Tables A.16 and A.17) demonstrate that although outcome magnitudes differ, the direction and key conclusions of the counterfactual analyses remain consistent.

8. Conclusion

It is well known that experts play an important role when consumers purchase complex and unfamiliar products and services, such as those in the financial and healthcare markets. To make an informed decision in such markets, consumers typically rely on experts with industry knowledge to provide recommendations. In this research, we focus on the healthcare market and study physicians' recommendations for their pool of patients when choosing a treatment facility.

This study proposes an empirical framework that econometrically recovers the experts' recommendations and models heterogeneous consumers' subsequent choice of products or services. Our framework distinguishes recommendations (first stage) and patient choices (second stage), mirroring real-world scenarios that are corroborated by insights from nephrologist interviews. We also show that an alternative single-stage framework yields a worse statistical model fit and unrealistic results, underscoring the importance of analyzing expert recommendations using a two-stage framework.

We then apply our framework to the U.S. dialysis industry, an important healthcare market that affects the lives of more than 500,000 patients. We estimate our model on detailed individual-level data of more than 16,900 new dialysis patients nationwide, their referring physicians, and their choice of treatment facilities between 2015 and 2017 and find that physician affiliation with a nearby treatment facility affects recommendation patterns; they favor their associated treatment facilities in terms of recommendations. We also find that the patient's choice of facility aligns with expectations; patients prefer facilities with higher star ratings that are closer to their homes. We also observe substantial patient heterogeneity in response to distances and star ratings. For example, we show that African American patients in lower-income areas are less responsive to star ratings. We find considerable variance in the match value, indicating significant uncertainty in a physician's assessment of the fit between patients and treatment facilities.

The model estimation enables us to study policies relevant to information provision and conflicts of interest in this market. Because mortality is generally high among the focal patients, we focus on mortality measures. We deploy a machine learning-based IV approach using artificial neural networks to mitigate selection bias and precision concerns in our measure of mortality.

We first evaluate the value of information provision via the CMS's dialysis facility star ratings by accounting for their impact on physician recommendations and the resulting patient choices and health outcomes. Our counterfactual results show that without the star ratings, the average mortality would increase by approximately 0.03%–0.15%, supporting the broader trend toward increasing information availability and transparency in the healthcare market.

We then consider the scenario of banning the usage of affiliation in recommendations as a consumer protection measure to mitigate physicians' potential conflicts of interest. Such a ban would hurt patients by increasing mortality by 1.1%. A possible explanation for this is that physicians in our data are more likely to be associated with higher-quality treatment facilities, making it less likely for those facilities to be recommended and later selected by patients if such a ban exists. This result suggests that policymakers and consumer advocates need to be mindful of the impact of physician affiliation before undermining it through legislative efforts similar to California Proposition 29 (2022) or a blanket ban.

There are limitations to our study. First, we acknowledge the data constraints in directly estimating the effect of waiting time. We use dialysis center utilization rate as a proxy for facility crowding, but more precise data on capacities and patient waiting times would be ideal, although we are not privy to such data in the U.S. dialysis market. Future research could explore distinguishing capacity constraints from the factors that attract patients that may be associated with high utilization rates. Second, the study does not fully assess the impact of physicians' self-interest, particularly for those with financial stakes in dialysis centers. This could lead to biased recommendations toward facilities where physicians might benefit financially. To explore this aspect thoroughly, detailed information on the financial relationships between physicians and treatment facilities would be required. The study suggests that future research should investigate the balance between physician familiarity with facilities and their potential self-interest beyond affiliation. We hope that our framework for recovering experts' recommendations helps consumers, managers, and policymakers better understand the role of experts in consumer choices and welfare.

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Endnotes

[1] See https://www.cdc.gov/kidney-disease/about/?CDC_AAref_Val=https://www.cdc.gov/kidneydisease/basics.html.

[2] See https://usrds-adr.niddk.nih.gov/2020/end-stage-renal-disease/9-healthcare-expenditures-for-persons-with-esrd.

[3] Five experts from urban and rural areas in three states were interviewed. In 2020, we interviewed a nephrologist by phone, a kidney transplant liaison in person at an Atlanta academic center, and another nephrologist virtually at a Dallas academic center. Two nephrologists at a rural academic center in central Texas were interviewed virtually in 2022. A final virtual interview with a nephrologist at a Maryland federal medical center took place in 2024.

[4] See https://healthcareappraisers.com/2020-outlook-dialysis-clinics-and-ESRD/.

[5] Medicare patients are generally charged a copayment of 20%, amounting to approximately $48 per dialysis session. We later use income as a way to capture affordability in our model.

[6] See https://data.cms.gov/provider-data/topics/doctors-clinicians.

[7] See https://www.medicare.gov/care-compare/.

[8] Patients may seek nonmedical quality measures, such as staff friendliness and parking availability, via online reviews. After reviewing Google reviews of a sample of treatment facilities, however, we noticed that many of these centers have zero, one, or at most two reviews during our data period (end of 2017). One possible reason is the patient population. The median age of the patients in our data is 72 years old, and they may not be tech savvy enough to write and read online reviews, especially prior to 2018.

[9] Gower is a dissimilarity measure between zero and one that measures how different two data points are (Tuerhong and Kim 2014). It is frequently used when dealing with data that have both continuous and discrete variables. We construct the dissimilarity measure based on quality measures, five-star rating, and the chain status of the centers included in a given recommendation set.

[10] Note that our approach is agnostic about the size and composition of the recommendations. In some cases, the balance between the benefit and the cost could result in just one center being recommended.

[11] One way to interpret the bias noted by Honka et al. (2019) is that unobserved, limited consumer information introduces omitted variable bias, leading to endogeneity. Our study, like Bronnenberg and Vanhonacker (1996), Goeree (2008), Ching et al. (2009), and Terui et al. (2011), addresses this by explicitly modeling limited information in a two-stage framework. Alternatively, this bias can be corrected in a single-stage model by employing instrumental variables, provided that suitable instruments are available.

[12] See https://www.cms.gov/newsroom/fact-sheets/dialysis-facility-compare-star-ratings-and-data-release.

[13] We use an ordered logit model to predict five-star ratings based on the ownership structure of a facility and the utilization rate (Γ_j), which were available before the launch of the five-star rating program.

[14] There have been studies in which they conduct policy simulations through changing econometrically estimated parameters. For example, Crawford and Shum (2005) simulate a no-learning scenario by eliminating perceived variances in drug efficacy, whereas Ching (2010) adjusts the generic drug entry intercept to analyze reduced approval times. Kim et al. (2010) compare limited and full consumer search by varying search costs, and Honka (2014) explores the effects of removing search and switching costs in auto insurance. Murry and Zhou (2020) recover unobserved search sets for car dealerships and conduct counterfactuals by changing search parameters.

[15] See https://flowtherapy.com/resource/what-is-the-survival-rate-of-coronary-artery-disease/.

[16] The CDC reports that 125,502 kidney patients passed away from mid-2015 to 2017 during our study period. Therefore, a 0.15% increase in mortality, for example, represents an additional 189 deaths over 2.5 years or approximately 76 deaths per year.

[17] An alternative policy would be to ban physicians from recommending any center with which they are affiliated (i.e., setting $A_j^k = -\infty$ rather than $A_j^k = 0$ in physician recommendation). Because this is a more stringent ban, the mortality change is greater. The policy simulation predicts a 2.6% increase in mortality because of the policy change, indicating that our main counterfactual analysis yields a more conservative estimate.

[18] For dialysis adequacy, the coefficient is 0.342, and for the case of anemia management, the coefficient is 0.312; both are statistically significant at 1%. For the mortality, the coefficient is –0.047 and statistically significant at 10%.

References

Anagol S, Cole S, Sarkar S (2017) Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market. *Rev. Econom. Statist.* 99(1):1–15.

Beckert W (2018) Choice in the presence of experts: The role of general practitioners in patients' hospital choice. *J. Health Econom.* 60:98–117.

Brennan TA, Rothman DJ, Blank L, Blumenthal D, Chimonas SC, Cohen JJ, Goldman J, et al. (2006) Health industry practices that create conflicts of interest: A policy proposal for academic medical centers. *J. Amer. Medical Assoc.* 295(4):429–433.

Bronnenberg BJ, Vanhonacker WR (1996) Limited choice sets, local price response, and implied measures of price competition. *J. Marketing Res.* 33(2):163–173.

Charoenwong B, Kwan A, Umar T (2019) Does regulatory jurisdiction affect the quality of investment-adviser regulation? *Amer. Econom. Rev.* 109(10):3681–3712.

Chen J, Chen DL, Lewis G (2021) Mostly harmless machine learning: Learning optimal instruments in linear IV models. Preprint, submitted June 18, https://arxiv.org/abs/2011.06158.

Ching AT (2010) A dynamic oligopoly structural model for the prescription drug market after patent expiration. *Internat. Econom. Rev.* 51(4):1175–1207.

Ching AT, Ishihara M (2012) Measuring the informative and persuasive roles of detailing on prescribing decisions. *Management Sci.* 58(7):1374–1387.

Ching J, Brown M, Burian S, Chen F, Cionco R, Hanna A, Hultgren T, et al. (2009) National urban database and access portal tool. *Bull. Amer. Meteorological Soc.* 90(8):1157–1168.

Claeskens G, Hjort NL (2008) *Model Selection and Model Averaging* (Cambridge University Press, Cambridge, UK).

Crawford GS, Shum M (2005) Uncertainty and learning in pharmaceutical demand. *Econometrica* 73(4):1137–1173.

Crawford GS, Griffith R, Iaria A (2021) A survey of preference estimation with unobserved choice set heterogeneity. *J. Econometrics* 222(1):4–43.

Dulleck U, Kerschbamer R (2006) On doctors, mechanics, and computer specialists: The economics of credence goods. *J. Econom. Literature* 44(1):5–42.

Eliason PJ, Heebsh B, McDevitt RC, Roberts JW (2020) How acquisitions affect firm behavior and performance: Evidence from the dialysis industry. *Quart. J. Econom.* 135(1):221–267.

Gaynor M, Propper C, Seiler S (2016) Free to choose? Reform, choice, and consideration sets in the English National Health Service. *Amer. Econom. Rev.* 106(11):3521–3557.

Goeree MS (2008) Limited information and advertising in the US personal computer industry. *Econometrica* 76(5):1017–1074.

Gowrisankaran G, Town RJ (1999) Estimating the quality of care in hospitals using instrumental variables. *J. Health Econom.* 18(6):747–767.

Guo T, Sriram S, Manchanda P (2021) The effect of information disclosure on industry payments to physicians. *J. Marketing Res.* 58(1):115–140.

Honka E (2014) Quantifying search and switching costs in the US auto insurance industry. *RAND J. Econom.* 45(4):847–884.

Honka E, Hortaçsu A, Wildenbeest M (2019) Empirical search and consideration sets. Dubé J-P, Rossi PE, eds. *Handbook of the Economics of Marketing*, vol. 1 (North-Holland, Amsterdam), 193–257.

Inderst R, Ottaviani M (2009) Misselling through agents. *Amer. Econom. Rev.* 99(3):883–908.

Kass RE, Raftery AE (1995) Bayes factors. *J. Amer. Statist. Assoc.* 90(430):773–795.

Kim TTI, KC D (2020a) Can Viagra advertising make more babies? Direct-to-consumer advertising on public health outcomes. *J. Marketing Res.* 57(4):599–616.

Kim TTI, KC D (2020b) The impact of hospital advertising on patient demand and health outcomes. *Marketing Sci.* 39(3):612–635.

Kim JB, Albuquerque P, Bronnenberg BJ (2010) Online demand under limited consumer search. *Marketing Sci.* 29(6):1001–1023.

Kim SM, Kim TT, Yoon TJ (2023) Does advertising matter to emergency patients? The effect of advertising on hospital choice, travel distances, and mortality rates. Preprint, submitted August 14, http://dx.doi.org/10.2139/ssrn.5147807.

Liu Q, Gupta S (2011) The impact of direct-to-consumer advertising of prescription drugs on physician visits and drug requests: Empirical findings and public policy implications. *Internat. J. Res. Marketing* 28(3):205–217.

Liu J, Huang Z, Gilbertson DT, Foley RN, Collins AJ (2010) An improved comorbidity index for outcome analyses among dialysis patients. *Kidney Internat.* 77:141–151.

Manchanda P, Xie Y, Youn N (2008) The role of targeted communication and contagion in product adoption. *Marketing Sci.* 27(6):961–976.

Mehta N, Rajiv S, Srinivasan K (2003) Price uncertainty and consumer search: A structural model of consideration set formation. *Marketing Sci.* 22(1):58–84.

Melanson TA, Gander JC, Rossi A, Adler JT, Patzer RE (2021) Variation in waitlisting rates at the dialysis facility level in the context of goals for improving kidney health in the United States. *Kidney Internat. Rep.* 6(7):1965.

Meyers DJ, Trivedi AN, Wilson IB, Mor V, Rahman M (2021) Higher Medicare Advantage star ratings are associated with improvements in patient outcomes: Study examines how Medicare quality ratings impact patient outcomes for those enrolled in Medicare Advantage. *Health Affairs* 40(2):243–250.

Murry C, Zhou Y (2020) Consumer search and automobile dealer colocation. *Management Sci.* 66(5):1909–1934.

Narayanan S, Desiraju R, Chintagunta PK (2004) Return on investment implications for pharmaceutical promotional expenditures: The role of marketing-mix interactions. *J. Marketing* 68(4):90–105.

Oshima Lee E, Emanuel EJ (2013) Shared decision making to improve care and reduce costs. *New England J. Medicine* 368(1):6–8.

Özer Ö, Subramanian U, Wang Y (2018) Information sharing, advice provision, or delegation: What leads to higher trust and trustworthiness? *Management Sci.* 64(1):474–493.

Prakash S, Coffin R, Schold J, Lewis SA, Gunzler D, Stark S, Howard M, Rodgers D, Einstadter D, Sehgal AR (2014) Travel distance and home dialysis rates in the United States. *Peritoneal Dialysis Internat.* 34(1):24–32.

Raval D, Rosenbaum T, Wilson N (2016) Industrial reorganization: Learning about patient substitution patterns from natural experiments. Preprint, submitted May 25, http://dx.doi.org/10.2139/ssrn.2784772.

Ryskina KL, Konetzka RT, Werner RM (2018) Association between 5-star nursing home report card ratings and potentially preventable hospitalizations. *Inquiry* 55:46958018787323.

Sakkas GK, Karatzaferi C (2012) Hemodialysis fatigue: Just "simple" fatigue or a syndrome on its own right? *Frontiers Physiology* 3:306.

Schwartz J, Luce MF, Ariely D (2011) Are consumers too trusting? The effects of relationships with expert advisers. *J. Marketing Res.* 48:S163–S174.

Shapiro BT (2020) Advertising in health insurance markets. *Marketing Sci.* 39(3):587–611.

Simonson I, Drolet A (2004) Anchoring effects on consumers' willingness-to-pay and willingness-to-accept. *J. Consumer Res.* 31(3):681–690.

Tamara Konetzka R, Grabowski DC, Perraillon MC, Werner RM (2015) Nursing home 5-star rating system exacerbates disparities in quality, by payer source. *Health Affairs* 34(5):819–827.

Terui N, Ban M, Allenby GM (2011) The effect of media advertising on brand consideration and choice. *Marketing Sci.* 30(1):74–91.

Tuerhong G, Kim SB (2014) Gower distance-based multivariate control charts for a mixture of continuous and categorical variables. *Expert Systems Appl.* 41(4):1701–1707.

Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. *Science* 185(4157):1124–1131.

U.S. Renal Data System (2023) 2023 USRDS annual data report: Epidemiology of kidney disease in the United States. Report, National Institutes of Health, National Institute of Diabetes and Digestive and Kidney Diseases, Bethesda, MD, 2023.

Velázquez AF, Thorsness R, Trivedi AN, Nguyen KH (2022) County-level dialysis facility supply and distance traveled to facilities among incident kidney failure patients. *Kidney360* 3(8):1367–1373.

Weiner DE, Meyer KB (2020) Home dialysis in the United States: To increase utilization, address disparities. *Kidney Medicine* 2(2):95–97.

Yoon TJ (2020) Quality information disclosure and patient reallocation in the healthcare industry: Evidence from cardiac surgery report cards. *Marketing Sci.* 39(3):636–662.

Yoon TJ, Kim TT (2024) The role of advertising in high-tech medical procedures: Evidence from robotic surgeries. *J. Marketing* 88(1): 97–115.