Market Power and Quality: Congestion and Spatial Competition in the Dialysis Industry*

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Abstract

Price regulation is an important feature of many health care markets. This paper develops a framework for investigating the role of price regulation in health care provider markets where policy interventions are often marked by tradeoffs between cutting costs, promoting clinical quality and improving access to care. Focusing on the U.S. market for outpatient dialysis I find that market structure affects clinical quality through two channels: Congestion and competition. Due to high travel costs, quality competition is relatively muted. However, as providers become more congested clinical quality suffers. Consequently market structure also affects quality through the allocation of patients across providers. I develop an entry model to endogenize market structure and disentangle these effects. The model is an entry game where dialysis providers make decisions about entry, capacity investment, and clinical quality. I estimate the model using data on approximately 400 million dialysis treatments in the U.S. and conduct counterfactual policy experiments. The results show that local market power allows providers to capture around 90% of a hypothetical increase in the Medicare reimbursement rate, leaving little pass through to patients in the form of improved quality. A travel subsidy program, which improves the allocation of patients, appears to be a more cost effective way of promoting quality. This proposed program costs the regulator $378 million but improves consumer surplus by $435.

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1 Introduction

Price regulation is an important feature of many health care markets. Understanding how price regulation affects health care providers and consumers is essential for informing policy. This is true in countries with universal health care programs (such as Canada, Germany, and Singapore), where prices are fixed by regulation. Price regulation also plays an important role in the U.S. where direct government payments account for 47.8 percent of all health care spending (Himmelstein and Woolhandler, 2016). This share is even higher in specific sectors such as nursing homes, where Medicare or Medicaid cover 75% of residents (Hackmann, 2018), and dialysis, where Medicare regulates rates for 80% of patients. Understanding how price regulation affects patients is important given these existing programs and also for informing the debate around new policies, such as a potential single payer system.

This paper presents a framework for studying competition among health care providers when prices are regulated. I focus on two ways that price regulation may affect patients. The first is competition. If prices are set low it may diminish providers' incentive to produce high quality care in order to attract more patients. Second, price regulation may affect patients through the extensive margin. Low regulated prices may result in low entry and capacity investment. Limited access to health care resources likely adversely affects patients by forcing them to travel farther, wait longer, or get treatments at less convenient times and locations. Fewer market participants may also mean reduced competition. Additionally, capacity constraints and congestion sometimes have indirect implications for clinical quality. This is the case in dialysis where providers face a quantity-quality tradeoff. As facilities with fixed dialysis capacity become more congested it becomes more difficult for providers to produce high quality care (Grieco and McDevitt, 2015).

Using data on close to the universe of dialysis treatments in the U.S. from 2001-2010, I present preliminary evidence linking the clinical quality provided at dialysis centers to market structure. I find evidence of a quantity-quality tradeoff—clinical quality and market share are inversely related and quality improves in dialysis capacity. I also find evidence of a competitive effect, as having a rival facility within 10 miles is associated with improved quality for a variety of patient outcomes. However, since market structure and capacity are endogenous this analysis may fail to identify a causal relationship. Motivated by this, I develop and estimate an entry game to model the non-random nature of market structure and use it to simulate policy counterfactuals.

My entry game allows for endogenous product competition on two margins: capacity and clinical quality. On the demand side, patients seek to maximize utility by balancing tradeoffs related to clinical quality, travel costs and congestion. On the supply side, firms seek to maximize expected profits by making decisions about entry, how much capacity to build, and how much clinical quality to provide. This model

allows me to simulate the expected long-run equilibrium effects of policies on market structure and welfare. I employ the model to explore the costs and benefits of policy interventions that increase the Medicare reimbursement rate, reduce private insurance rates to the same level as Medicare rates, subsidize entry, and subsidize patient travel costs. Incorporating the extensive margin into equilibrium outcomes in health care is an important, though often overlooked, consideration since the incentives governing quality provision likely interact with those governing entry and capacity investment.

Counterfactual simulations demonstrate that providers are able to exploit local market power to capture around 90% of the pass through from an increase in the Medicare reimbursement rate in the form of increased profits, leaving little pass through to patients in the form of improved access or clinical quality. A proposed travel subsidy plan proves to be a more cost effective way of improving consumer surplus and clinical quality. The subsidy results in reduced entry and dialysis capacity, but also reduced congestion, because patients are able to better allocate to less-congested providers. This freedom of movement forces providers to transfer profits to patients in the form of higher clinical quality.

Dialysis is a life-sustaining treatment for patients with kidney failure. Currently, over 460,000 people in the U.S. receive regular dialysis treatments. About 80% of these patients are enrolled in Traditional Medicare, which spends $33 billion a year to treat them—1% of the entire federal budget (Ramanarayanan and Snyder, 2014).[1][2] Medicare is dominant because almost all long-term dialysis patients qualify for Medicare regardless of age under the End-Stage Renal Disease (ESRD) program.

This market is ideally suited for studying the effect of price regulation on market structure and patients for a number of reasons. First, prices are mostly set administratively and competition must focus on other margins, such as quality. Despite Medicare's dominance, commercial insurance plays an important role because it pays much more than Medicare. The geographic dispersion of patients with differing payers provides important variation in realized market structure. Second, patients face high travel costs contributing to an imperfectly competitive market. Third, dialysis technology limits the capacity of providers and results in congestion externalities for patients. The number of dialysis stations at each facility provides a clean way to measure capacity. Fourth, rich data on patient severity, provider attributes, and clinical outcomes enable estimation.

The data used to conduct this research come from the U.S. Renal Data System (USRDS). It contains records for approximately 400 million dialysis treatment events for over 1.2 million dialysis patients. These data include residential and treatment histories for nearly all dialysis patients in the U.S., regardless of

[1] 2016 Annual Data Report, US Renal Data System

[2] These patients make up just 1% of the Medicare population, but are responsible for a disproportionate 7.2% of Medicare's claims costs.

payer.[3] This allows me to observe the quantities served by each provider, estimate heterogeneous patient preferences for provider attributes, and assess the quality of care by using blood-chemical tests directly measuring clinical quality as well as patient outcomes such as mortality and hospitalization.

My model exploits variation in the geographic distribution of patients and their insurance type, as well as observed provider actions, to draw inferences about the economic incentives facing potential entrants. On the demand side, I estimate a discrete choice model of dialysis facility choice. Patient utility depends on distance, clinical quality, and congestion, among other things. To instrument for clinical quality and congestion, which are likely endogenous, I use predicted counts of Medicare and privately insured patients at each facility based only on exogenous geographic data. On the supply side providers play a game in which they form expectations over rival actions and demand realizations when choosing their own strategies. Strategic variables include entry, capacity, and quality decisions. In the model, they make entry and capacity decisions simultaneously. After entry and capacity are realized, they compete on quality. Capacity affects provider profits in three ways. First, fixed costs increase in capacity. Second, capacity directly allows them to see more patients. Third, the marginal cost of quality decreases in congestion. The optimal quality decision will depend on the quality elasticity of demand and the marginal cost of quality.

I use the model to simulate counterfactuals that explore several potential Medicare reforms of the ESRD program. The most cost-effective reform is a policy that subsidizes the travel of dialysis patients. This policy diminishes the market power of dialysis providers by making geographically differentiated providers more substitutable. This increases quality competition resulting in both less entry and improved quality. Overall, these subsidies result in 5.6 percent fewer providers entering and increases the average risk adjusted survival rate by 0.4 percentage points, resulting in 1,564 fewer deaths each year. I estimate that this subsidy program would cost $378 million dollars each year but increases consumer surplus by $435 million (a 31 percent increase). I also find that policies increasing payments to dialysis providers, either by increasing the Medicare reimbursement rate or subsidizing entry, can produce better outcomes for patients. However, these programs are very expensive ways to increase consumer surplus because providers capture around 90% of the pass-through from these programs in the form of producer surplus. If the regulator cares about consumer surplus and fiscal responsibility more than producer surplus, then they should favor policies that diminish provider market power. By decreasing providers' market power the regulator can assure that a greater portion of spending gets through to patients in the form of better care.

This paper provides a link between the literature on capacity investment as a strategic variable and the literature on quality competition in health care. A number of theoretical and empirical papers treat the effect of capacity investment choices on the competitive nature of markets (Dixit (1980), Kreps and Sheinkman

[3]The main group of patients excluded from the data are those who only need dialysis for short periods of time.

(1983)). However, the empirical literature usually links capacity to welfare abstractly or sometimes, as in the context of health care, through access (Dai and Tang (2014), Gowrisankaran et al. (2017), Ching et al. (2015)). I extend this literature by explicitly modeling capacity decisions that affect patients directly through congestion and indirectly by influencing quality choices.

In the extensive literature on quality competition in health care, theoretical models have long shown that imperfect competition can lead to non-optimal quality levels (Spence, 1975). Numerous empirical studies support this, especially in the case of administratively set prices (Kessler and McClellan (2000), Bloom et al. (2015), Gaynor et al. (2013), Hackmann (2018)).[4] I contribute to this literature by modeling the extensive margin and incorporating congestion into the quality decision as providers face a quantity-quality tradeoff. A similar concept has been studied in other markets such as electricity where fluctuations in demand and fixed grid capacities result in higher prices when demand spikes (Borenstein et al., 2002). Additionally, this literature usually assumes a fixed number of firms or capacity. This is problematic for counterfactual analysis where the market structure itself may be influenced by regulation. I relax this assumption and endogenize the supply of providers and capacity.

More broadly, this paper draws on structural methods from industrial organization and applies them to the health care sector. Specifically, it employs a model of endogenous product entry, largely influenced by existing models such as Mazzeo (2002) and Seim (2006). While such models have been used in health care (e.g. Lin (2015), McDevitt and Roberts (2014)), their use is sparse. This is one of the first such papers where potential entrants choose multiple strategic variables.

Finally, there is a small but growing literature about the economics of dialysis. Four papers are closely related to this work. Dai and Tang (2014) study the capacity choices of entering dialysis providers and consider counterfactuals that include decreases in Medicare payment levels. Grieco and McDevitt (2017) estimate a quality-quantity trade-off and conclude that dialysis providers can increase the number of patients they treat, without additional inputs, but it comes at the cost of quality to the patients. Cutler et al. (2015) find little, if any, evidence of a relationship between market concentration and quality. Eliason et al. (2018) investigate the transference of clinical practices when clinics are acquired by corporations and how this affects Medicare costs, quality of care, and patient outcomes. I extend this literature in a number of ways. First, my rich data set allows me to better measure dialysis quality, better identify patient preferences, estimate the effect of facility congestion on demand, and analyze competition on a very localized level. Finally, my structural model produces a policy function that describes clinical quality decisions and how they are influenced by capacity investment and the competitive nature of the local market.[5]

[4] For a more thorough review see Gaynor et al. (2015).

[5] For other papers about the economics of dialysis, see Dai (2014), Wilson (2016a), Wilson (2016b), and Ramanarayanan and Snyder (2014).

The remainder of this paper proceeds as follows. Section two provides some background on the institutional details of the dialysis industry. Section three presents the data. Section four provides a preliminary analysis motivating my model. Section five describes the model. Section six details estimation. In section seven I present and discuss the model estimates and in Section eight I present the counterfactual results. Finally, section nine concludes.

2 Background

2.1 Kidney Failure and Dialysis

Dialysis replaces the function of kidneys that have failed by filtering wastes and toxins out of the blood. This function is necessary to sustain life.[6] End-stage renal disease (ESRD) is the general diagnosis given to patients with chronic kidney failure. There are two treatments for ESRD: kidney transplantation or dialysis. While transplantation is considered the preferred option, it is often unavailable due to the scarcity of kidneys. Fewer than 20% of dialysis patients qualify for kidney wait lists, and for those who do, the median wait time for a kidney is 3.6 years.[7] Consequently, most patients with kidney failure rely on dialysis permanently or for an extended period. In 2014, there were 460,000 dialysis patients in the U.S.

Dialysis patients can choose among different modalities, or types, of dialysis. The most popular is in-center hemodialysis. Over 90% of patients use this. These patients report to a facility dedicated to dialysis where their blood is artificially filtered by a machine and returned to their body. The standard regimen of care is to receive three treatments a week, each one taking between two and five hours. Some patients find home dialysis preferable to in-center dialysis. Being treated at home allows patients to be treated more frequently or at more convenient times (e.g., nocturnal dialysis). However, home treatment is less popular. Reasons for this are the perceived costs associated with having dialysis equipment installed and operated at one's home and the challenges and discomfort of self-management (Cafazzo et al. (2009) and Yau (2016)).

2.2 Quality in Dialysis

Generally, quality refers to aspects of a good or service, other than price, that affects the consumer's utility. In the outpatient dialysis market, quality can be decomposed into two components: clinical quality and amenities. Nonclinical amenities are an important aspect of competition in the dialysis industry. Gupta (2007) describes competition among dialysis facilities to include heated massage chairs, aroma therapy,

[6] On average, patients with kidney failure who forgo treatment live 10 days, according to the National Kidney Foundation (`https://www.kidney.org/atoz/content/dialysisstop`).

[7] 2014 Annual Data Report, US Renal Data System

birthday celebrations, bingo, night shifts, and more. Unfortunately, these features are often difficult to measure.

Clinical quality in health care is often difficult to measure. In dialysis, however, data are available that closely gauges the quality of each treatment. In my analysis I include three metrics that directly asses the clinical quality at dialysis facilities and two that gauge patient outcomes more broadly. The direct measures of clinical quality assess the quality of dialysis itself, anemia treatment, and infection control. The broader outcomes I study are survival and hospitalizations. CMS rates dialysis facilities on how well they perform on each of these five dimensions. They then post coarse statistics of them to the Dialysis Facility Compare Website,[8] in an effort to educate patients about their options of providers.

Dialysis quality can be assessed using the urea reduction ratio (URR). Urea is one of the primary wastes dialysis filters from the blood. URR is the percent of urea filtered out of a patients blood during dialysis. This measure comes from blood chemical tests administered before and after dialysis. The results of these tests are then used to compute the percent reduction in urea:

$$URR = \frac{Urea_{\text{Before dialysis}} - Urea_{\text{After dialysis}}}{Urea_{\text{Before dialysis}}}$$

One benefit of this quality measure is that providers have direct control over it. As long as the provider is using the dialysis equipment properly, the patient's URR will approach one the longer a patient is on a dialysis machine . Different patients need differing amounts of time to get the same URR. As a standard of care, a dialysis session should achieve a URR of at least 0.65.[9]

The second indicator of clinical quality assesses anemia treatment. Anemia is the condition of having a low red blood cell count. It can cause patients to suffer a range of symptoms, from fatigue to death. It is very common among dialysis patients. A blood test for hemoglobin (HGB) levels measures the severity of anemia. The FDA recommends treating to a HGB level between 10 and 12g/dL (grams per deciliter).[10] Patients with HGB below 10g/dL are anemic. Patients treated to levels that are too high can also experience complications such as cardiovascular events (Besarab et al. (1998) and Singh et al. (2006)).[11]

The third measure of clinical quality is dialysis-related infections that provide information about the

[8] `https://www.medicare.gov/dialysisfacilitycompare/`

[9] This is according to the National Institute of Diabetes and Digestive and Kidney Diseases. See `https://www.niddk.nih.gov/health-information/kidney-disease/kidney-failure/hemodialysis/dose-adequacy`.

[10] See `https://www.fda.gov/Drugs/DrugSafety/PostmarketDrugSafetyInformationforPatientsandProviders/ucm126481.htm`

[11] Anemia is treated with drugs, which are often administered to patients as injectibles in dialysis facilities. HGB levels take time to respond to treatment and each patient requires idiosyncratic doses but, over time, dialysis providers have control over a patients HGB levels. Incentives to overtreat or undertreat patients for anemia change throughout the years. Before 2011, Medicare reimbursed for EPO use, the most common anemia drug, based on how much of the drug was used. This created strong incentives to over treat. Starting in 2011 anemia treatment and dialysis were bundled into a single prospective payment system. Since then, providers have faced an incentive to cut costs by undertreating. This issue is treated more extensively in Eliason et al. (2018) but the anemia treatment quality is included here for completeness.

infection control practiced by facilities. Dialysis patients are especially susceptible to infection because of weakened immune systems and the nature of their treatment requiring frequent and direct access to the blood stream. Consequently, sanitation and infection control is a major concern for providers (Zumoff, 2016), who can significantly reduce infections through proper practices and procedures (Patel et al., 2013). However, infection control is costly. It can take up to one hour to follow proper procedures to clean and prepare each dialysis station for the next treatment (Grieco and McDevitt, 2017). The frequency of observed hospitalizations for dialysis-related infections can proxy for the quality of infection control at each facility.

I also consider survival and hospitalization as broader sufficient statistics of the care received in these centers. While these outcomes may be co-determined with the above-mentioned quality measures and unobserved factors outside of the provider's control, such as patient severity or adherence, they are of primary importance from a welfare perspective and will likely capture valuable dimensions of care missed by the direct quality measures.

2.3 The Provider's Role in Clinical Quality

Decisions made by providers at dialysis facilities have a direct impact on clinical quality and outcomes. Workers at these facilities mainly include a medical director, facility administrator, nurses, and dialysis technicians. Every facility is required to have a medical director, a physician, who is responsible for the performance and reliability of care at the facility. While they have this liability they are not required to be present at the facility and the day-to-day operations are largely run by a facility administrator. The role and background of facility administrators vary. Sometimes they are more of a head nurse and sometimes they are more of a business administrator.

Most patient care is performed by nurses (registered nurses or advanced practice nurses) or dialysis technicians. The requirements to be a dialysis technician generally include a high school diploma and a one year certification program. Much of their training is on-the-job at the dialysis facility. Facility administrators can influence quality through how they allocate capital and labor. By committing more time on a dialysis station to patients, providers can achieve higher URRs. By using more labor to clean and disinfect they can achieve lower infection rates. By using more skilled labor (more nurses or more training) they can also get better outcomes and fewer mistakes. They can also improve quality through additional inputs, such as staff training.

Capacity choices affect clinical quality because congestion makes quality more expensive. The more patients per station a facility experiences, the more intensely its capital must be utilized. This is costly and can only be done by increasing other inputs, such as labor (i.e. paying more people to stay open longer).

2.4 Policies and Prices

Medicare plays a central role in this industry. Since 1972, all ESRD patients have been Medicare eligible, regardless of age. Traditional Medicare is the primary payer for close to 70% of dialysis patients in the U.S. Medicare Advantage covers an additional 20% and private insurance covers only about 7%. Medicare pays for dialysis using a prospective payment system (PPS). A fixed base rate is adjusted based on geographic factors, such as the wage index, and patient cost-adjusters. Under this policy, providers internalize the actual costs of dialysis provision. Prior to 2011, injectible anemia drugs were separately billable. However, in 2011 this was combined with dialysis into a single prospective payment bundle. In 2012, CMS began the Quality Incentive Program (QIP), which ties payments to quality by penalizing facilities with low URR outcomes or unacceptable hemoglobin levels.

CMS has tried to cut dialysis expenditures through what they call a private insurance coordination period. Patients under 65 who have private insurance when they begin dialysis keep their private insurance as their primary payer for the first two and a half years of dialysis. When this coordination period ends the patient is switched over to Medicare as the primary payer. According to one annual report, these commercial payers have rates that are "significantly higher than Medicare rates."[12] Included in Appendix A is a graphic from a DaVita presentation showing estimates that private insurance payers make up 10% of their caseload but 100% of their profits, while Medicare rates are 10-15% below cost.

2.5 Industry Details

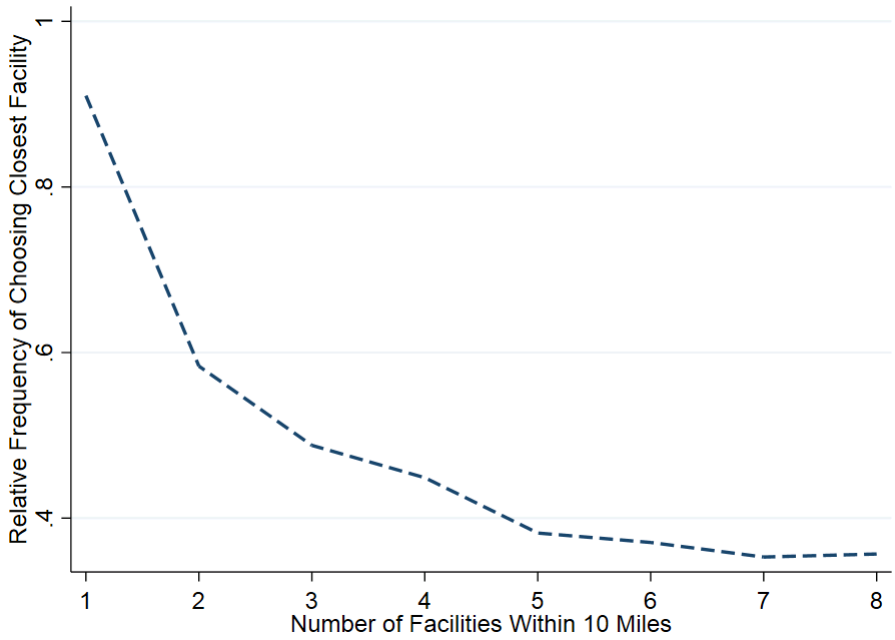
In recent decades the dialysis industry has undergone a dramatic increase in concentration. In 1988 14% of dialysis centers were chain-affiliated (Pozniak et al., 2010). By 2012 chains controlled 76% of facilities. All but one of these are for-profit companies. The two largest chains are publicly traded companies DaVita and Fresenius, which control over 63% of dialysis facilities(USRDS, 2014). This concentration has increased through both acquisitions but also through opening new facilities. Between 1998 and 2012 the total number of dialysis facilities grew from 3,576 to 6,284. When deciding where and when to open or buy a facility, a major consideration these companies make is how many privately insured patients there are (Neumann, 2016).

2.6 Demand For Dialysis

Based on discussions with dialysis facility administrators, patients, and nephrologists, as well as a review of qualitative studies of the subject, there are four major factors patients consider when choosing

[12]DaVita Annual Report, 2013, page 101

Figure 1: Observed Probability of Choosing the Closest Facility



a facility for dialysis treatments: Location, clinical quality, congestion, and miscellaneous amenities. The first, location, is generally thought to be the most important consideration. This horizontal preference is particularly pronounced because dialysis patients are often not very mobile. The effects of dialysis leave many patients uncomfortable driving home after treatment. Consequently, they often rely on family members, public transportation, ambulances, or shuttle services to get to and from the clinic, meaning travel costs are high. However, in the data I observe that 64% of dialysis patients forgo their closest facility for treatment. Figure 1 shows that the frequency of choosing the closest facility falls as the number of alternatives within 10 miles increases. This suggests that there are other attributes playing a role in the choice process.

Clinical quality is potentially another important factor. Research suggests that dialysis patients have some sense of the quality provided at dialysis facilities (Ramanarayanan and Snyder, 2014). Various efforts have been made to inform patients. Dialysis Facility Reports have been produced for each facility annually since 1995, under contract from CMS. These reports combine information from surveys conducted about facilities and outcomes gleaned from Medicare claims and death records. They are intended to be used to inform and motivate dialysis providers, as well as to inform dialysis patients about their potential providers. A major vehicle to disseminate this information is the Dialysis Facility Compare website[13], where patients can look up and compare various measure of quality for all of the providers in a certain region. Another source of information available to patients is through their referring physicians. I interviewed multiple nephrologists who regularly referred new dialysis patients to facilities. Each of them expressed that, while they didn't feel

[13] www.dialysisfacilitycompare.com.

like they knew which dialysis facility offered the best treatment, they did have in mind a list of facilities that they would warn patients against because of a reputation for shoddy service.

Another factor when choosing a dialysis facility is congestion. Congestion matters in two ways. First, externalities from crowded facilities generate disutility to patients. This can come from wait times, less attention from employees that are spread thin, a noisy or hectic environment, and other things. Second, as congestion rises patients face less flexible schedules and in some cases may not be able to get in at all.[14] Potential capacity for a dialysis facility is limited by the number of dialysis stations. However, identifying the exact constraint is difficult for a variety of reasons, including unobserved differences in patient case-loads, heterogeneity in dialysis machine technology, and hours of operations. Rather than model capacity constraints as a binary variable, I use the continuous measure of patients per dialysis station. This can also be thought of as a congestion effect. This also allows it to capture the aforementioned disutility from crowding.

A wide variety of other amenities may also play a role in patient choice. These may include cable TV, reclining chairs, free snacks and juice bars. This may also include transportation factors not captured in travel distance, such as proximity to an on-ramp or bus station. Due to a lack of data, I abstract away from focusing on this dimension and rely on the use of instruments to control for this as a component of unobserved quality. We may also want to include price in the set of patient preferences. However, since Medicare sets the price for such a large portion of the market and commercial insurance covers the rest, patients are unlikely to experience much variation in out-of-pocket expenses[15].

3 Data

This analysis relies on a comprehensive data set provided by the US Renal Data System (USRDS).[16] USRDS combines data from three sources: Medicare administrative files, the Consolidated Renal Operations in a Web-Enabled Network (CROWN)[17], an annual facility survey, and the Social Security Master Death File. Combined these contain data on nearly all ESRD patients in the US, including those who are not Medicare beneficiaries,[18] and all dialysis facilities. For more details about the data and how it was formatted for this

[14] One patient said, "I tried first to get into [another facility] but they were booked up and there were no openings, there was an opening there.... I'd like to switch to [previously mentioned facility]" (Morton, 2010). One facility administrator said, "There's been some growth and that puts us right at 96% of out capacity.... We can't always meet their particular personal needs, as far as scheduling times..." (Fargen, 2016).

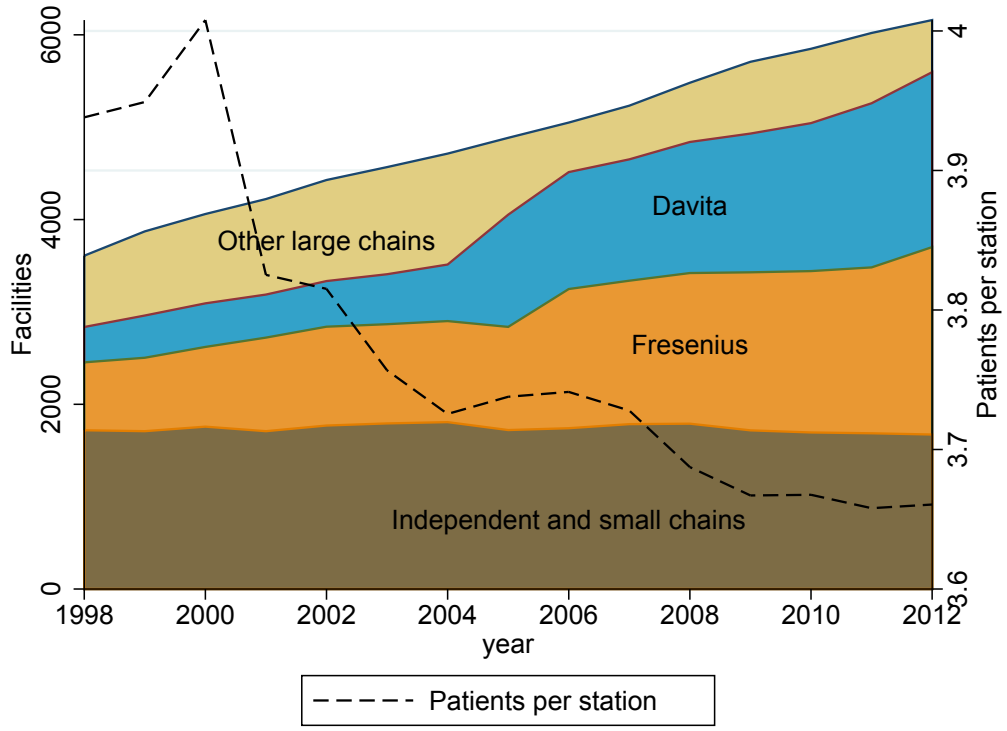
[15] Variation in out-of-pocket expenses may play a role for the commercial market as patients are encouraged to remain in-network. This is a relatively small portion of the market from which I abstract.

[16] See `www.usrds.org`.

[17] Employees at dialysis facilities report data about patients, diagnostics, and treatments into this system. These data contain the location, modality, and date of almost every dialysis treatment administered to patients in the U.S.

[18] CMS requires the Medical Evidence Form for all patients starting dialysis, regardless of payer. The purpose of this form is to establish a date when Medicare becomes the primary payer for each patient. This form, combined with the CROWN data can establish a treatment history for non-Medicare patients.

Figure 2: Industry Growth



analysis see Appendix Section B. I focus my analysis on the years between 2001 and 2010. I do not extend the analysis period beyond 2010 because in 2011 there were a number of major changes to how Medicare reimburses for dialysis.[19]

3.1 Patient data

Patient summary statistics are found in Table 1. The average patient starts dialysis at 59.5 years of age, below the typical age of Medicare eligibility. On average patients spend ## years on dialysis. Slightly more than half of them are male, 36% are black, and 14% are Hispanic. Only 14% are employed when they begin dialysis. On average, patients live 6.4 miles from the dialysis facility where they are first treated. The clinical characteristic statistics show that these patients typically have poor health. More than half are diabetic, 82% are hypertensive and 29% have congestive heart disease. The average BMI is 28.5.[20]

In the first year of dialysis 9% of patients have private insurance as their primary payer and just under 72% have Traditional Medicare. By the beginning of the fourth year on dialysis the share of patients with private insurance a virtually vanished, having moved to Medicare when the 30 month coordination period

[19] These include the combining of payment for dialysis and injectible drugs into a single "prospective" payment, a major reformation of patient-specific payment adjustments, and a pay for performance policy, the Quality Incentive Program, implemented in 2012.

[20] A BMI of 25 to 29.9 is considered "overweight" and a BMI of 30 or above is "obese."

Table 1: Patient Summary Statistics (2001-2010)

	Mean	St. Dev.
Demographics		
Age at Dialysis Initiation	59.54	(16.07)
Years on Dialysis	2.91	(3.18)
Male	0.55	(0.50)
Black	0.36	(0.48)
Hispanic	0.14	(0.35)
Non-Hispanic White	0.44	(0.50)
Other Race	0.05	(0.22)
Employed at Dialysis Initiation	0.14	(0.35)
Travel Distance (Miles)	6.42	(5.85)
Clinical Characteristics		
Diabetes	0.52	(0.50)
Hypertension	0.82	(0.39)
Vascular Disease	0.12	(0.33)
Congestive Heart Disease	0.29	(0.45)
Glomerular Filtration Rate	8.27	(5.21)
BMI	28.47	(7.78)
Primary Payer in First Year		
Traditional Medicare	0.72	(0.45)
Medicare Advantage	0.11	(0.31)
Private Insurance	0.09	(0.28)
Other	0.08	(0.50)
Primary Payer in Fourth Year		
Traditional Medicare	0.85	(0.36)
Medicare Advantage	0.08	(0.27)
Private Insurance	0.00	(0.06)
Other	0.06	(0.26)
Number of Unique Patients	1,201,904	
Number of Patient*Year Observations	3,773,693	
Number of Treatment Events	400 Million	

Notes. The glomerular filtration rate is a measure of residual kidney function. It measures how much blood is filtered by the kidneys each minute. A general rule of thumb is that patients should begin dialysis when their glomerular filtration rate is below 15mL/min. The payer category "other" includes patients with Medicaid (but not Medicare), TRICARE, uninsured, and with an unknown payer.

lapsed.

3.1.1 Patient Outcomes

I focus on five patient-level outcomes contained in the data. Four of these outcomes are only available for Medicare patients, as they are sourced from Medicare claims. The fifth outcome, survival, comes from the Social Security Master Death File and is available for all patients, regardless of payer.

In the structural model, I use the risk-adjusted survival rate as a sufficient statistic for each facility's clinical quality. However, I present preliminary results showing how market structure seems to affect each of five distinct risk-adjusted measures of clinical quality: survival, hospitalizations, septicemia infections, dialysis adequacy rates, and the rate of "Good Anemia Treatments."

I construct annual measures of each of these five outcomes. Survival is coded as a one for every patient alive on December 31st of the year. I use the Medicare claims to identify episodes of hospitalization and compute a count of hospitalizations within each year for each patient. I construct episodes of hospitalization in a way that combines inpatient stays at different hospitals into the same episode as long as the patient didn't spend at least one day outside of an inpatient facility. Third, I evaluate infection control by using the Medicare claims to identify episodes of hospitalization where patients were hospitalized for either a septicemia infection as the primary diagnosis.[21] I then construct a count of hospitalizations for septicemia for each patient and year.

I directly evaluate the adequacy of dialysis treatments using Urea Reduction Ratios (URR) reported in the Medicare claims. URR directly measures how well each dialysis treatment cleaned the patient's blood. These measures are available only for Medicare beneficiaries. I collapse these to a yearly frequency by computing the percent of treatments that resulted in a URR over 65 for each patient:

$$y_{ijt}^{URR} = \frac{\text{Number of treatments with URR>65}}{\text{Total number of treatments}}.$$

Finally, I assess anemia management using monthly HGB tests found in the Medicare claims. I collapse these to an annual frequency in the same way I did with URR, categorizing patients as well-treated for anemia if their HGB levels are between 10 and 12 g/dL.

Table 2 shows raw summary statistics for these outcomes. The average annual survival rate in the data is 83%. The average patient is hospitalized 1.97 times each year and 0.08 times for septicemia infection. The average dialysis adequacy rate is 88%. This means that on average, 88% of a patient's dialysis treatments results in a URR above 0.65. The average patient is properly treated for anemia 47% of the time.

[21] See Appendix Section B.2 for details on how these were coded.

Table 2: Patient Outcome Summary Statistics

	Mean	Std. Dev.
Annual Survival Rate	0.83	(0.38)
Hospitalizations	1.97	(2.34)
Hosp. for Infection	0.08	(0.32)
Dialysis Adequacy Rate	0.88	(0.23)
Good Anemia Treatment Rate	0.47	(0.28)
Patient*Year Observations	3,773,693	

Notes: Summary statistics from data with one observation for each patient and year. Sample spans years 2001 to 2010.

3.2 Facility Data

Table 3 displays the facility summary statistics. The average facility treats 62.8 patients and has 17.7 dialysis stations. Each day the facilities treats 1.7 patients per station on average. The standard deviations of patients per station is 0.8, suggesting a substantial among of variation in congestion at these facilities. Figure 2 shows that chain presence in the industry is growing over time. While 71% of the facility-year pairs in my data are affiliated with a dialysis chain, in 2010 this number was 76%. The Figure also shows that on aggregate, dialysis capacity measured by stations, is growing faster than demand.

Table 3: Facility Summary Statistics

	Mean	Std. Dev
Number of Patients	62.80	(43.07)
Number of Dialysis Stations	17.69	(8.27)
Number of Employees (FTEs)	12.93	(8.56)
Patients per Station (per Day)	1.72	(0.80)
Chain Owned	0.71	(0.46)
Davita	0.23	(0.42)
Fresenius	0.29	(0.45)
For-profit	0.78	(0.41)
Freestanding	0.88	(0.32)
Facility Age	11.52	(8.85)
Observations	45,001	

Notes. Data spans the years 2001 through 2010 (except data on labor). Summary statistics are of a panel dataset with each observations representing a facility in a specific year. Data on employees begins in 2004.

3.2.1 Facility Quality

Assessing facility quality is central to this analysis. I focus on outcomes and aspects of clinical quality since they are a major part of the value being provided by dialysis facilities. I risk adjust the outcomes described in the previous section and estimate facility-level "value-adds" for each year. This method is similar to that used by Chandra et al. (2016) and is commonly used to evaluate teacher or school quality in the education literature (Rivkin et al. (2005) and Chetty et al. (2014)). The idea is to isolate the performance of each facility after accounting for the non-random sorting of patients. I proceed by estimating the following equation:

$$y_{ijt} = X_{it}\beta + \mu_{jt} + \varepsilon_{ijt}, \tag{1}$$

where i indexes patients, j indexes facilities, and t indexes years. The dependent variable, y_{ijt}, is one of the clinical outcomes. This is regressed on an array of patient risk-factors, X_{it}, and a facility-year constant. The facility-year constants, μ_{jt} are then recovered and interpreted as provider value-adds. The assumption here is that the mean difference between the observed outcomes and risk-adjusted expected outcomes at a facility can be attributed to that facility's efforts or inputs. Estimates from the value-add regressions can be found in Appendix Table 18. Summary statistics of the value adds can be found in table 4.

Table 4 shows that there is substantial variance in the distribution of facility quality. The top panel shows raw summary statistics of outcomes by facility. The bottom panel contains summary statistics for the risk-adjusted facility outcomes—the value adds. The standard deviations describe the dispersion of quality. Given two facilities with the same patient risk profile, a difference in survival quality of one standard deviation corresponds to a difference in expected survival rates of 0.08. Likewise, one standard deviation in dialysis quality corresponds to a 12.7 percentage point difference in the probability of getting good dialysis treatment. Thus there is meaningful dispersion in the distribution of quality. In the analysis that follows I standardize the value adds by dividing by the standard deviation and call them quality scores.

Table 4: Facility Quality

	Mean	Std. Dev.
Unadjusted Mean Outcomes		
Survival	0.83	(0.09)
Hospitalizations	1.76	(0.53)
Hosp. for Infection	0.08	(0.07)
Dialysis Adequacy Rate	0.88	(0.10)
Good Anemia Treatment Rate	0.47	(0.12)
Facility Risk-Adjusted Outcomes		
Survival	0.83	(0.08)
Hospitalizations	1.79	(0.52)
Hosp. for Infection	0.07	(0.06)
Dialysis Adequacy Rate	0.88	(0.09)
Good Anemia Treatment Rate	0.46	(0.12)
Observations	45,001	

Notes. Based on sample spanning 2001 to 2010.

3.3 Dialysis Prices

The Medicare claims data provide payments from Medicare to dialysis providers. These payments can be split into three components: dialysis, EPO, and other separately billable items. Table 19 in the appendix breaks these down. Dialysis is the largest portion of these payments although payments for Epogen are also substantial. On average, dialysis facilities receive $238 each time they treat a Medicare patient. I do not have data on private insurance prices. It is well documented that private insurance pays much more than Medicare but there appears to be a lot of variation in how much more (Cutler et al., 2015). What sources on private insurance prices are available find that private insurance typically pays at least twice as much as Medicare (USRDS (2010), Shinkman (2016), Cutler et al. (2015)).

4 Preliminary Evidence

4.1 Determinants of Quality

In this section I present a preliminary analysis describing the relationship between market structure and clinical quality in the dialysis industry. I focus on two channels through which market structure may affect clinical quality: Competition and congestion. In other settings, researchers have looked for evidence of a positive correlation between market share and productivity as a sign of an incentive to compete.[22] In

[22]This has been done to study the steel industry (Collard-Wexler and DeLoecker, 2015), telecommunication equipment (Olley and Pakes, 1996), and manufacturing (Bartelsman et al., 2013), among others.

health care, Chandra et al. (2016) use quality to measure hospital productivity. They reason that when consumers bear little of the cost of production, competition likely occurs on provider performance. The intuition is that if demand allocates to high quality providers the low quality providers may be forced to exit, shrink, or become more efficient.

While competition may induce a positive correlation between market share and clinical quality, previous research has found evidence of a quantity-quality tradeoff in dialysis. Grieco and McDevitt (2015) show that because dialysis providers have fixed capacity, at least in the short run, the act of treating additional patients may come at the cost of lower clinical quality care. Thus market share and clinical quality may be simultaneously determined, with market share affecting quality through a quantity-quality tradeoff and quality affecting market share as patients seek to allocate to higher quality providers.

To unpack the determinants of quality, I estimate the following equation:

$$\mathcal{Q}_{jmt} = \beta_0 + \beta_1 N_{jt} + \beta_2 \mathbb{1}(\text{Has rival withing 10 miles}) + X_{jmt}\Gamma + u_{jmt} \tag{2}$$

where $\mathcal{Q}_{jmt}$ is a measure of clinical quality at facility j in market m and year t. The principle explanatory variables of interest include the number of patients treated at the facility, N_{jt}, and an indicator for whether or not the facility has a rival facility within a 10 mile radius. Both of these variables are endogenous.

As described above, the size of a facility's patient case load will affect quality through a congestion affect. However, potential reverse causation may result in a biased estimator for β_1. In particular, if patients allocate to better providers this would induce a positive correlation between $\mathcal{Q}_{jmt}$ and N_{jt} and result in a positive bias in the estimator for β_1.

To identify the effect of the size of a patient case-load on clinical quality, I use an instrumental variables strategy. To instrument for N_{jt} I construct predicted patient case-loads for each facility based solely on the geographic distribution of patients and facilities. I do this by estimating a multinomial logit model of facility choice based only on the distances from each patient to the other facilities within 30 miles of the centroid of their ZIP code of residence. I then use this estimated model to predict facility case-loads.

The resulting predicted patient counts prove to be strongly correlated with the actual patient counts, as shows in Table 5 which describes the first stage results for the IV estimators. The exclusion restriction relies on the assumption that patients and facilities do not collocated for reasons related to or correlated with clinical quality. To improve on the plausibility of this assumption, I assign patients to their location of residence when they initiated dialysis. With this adjustment, exclusion depends on the somewhat weaker assumption that patients and facilities don't collocate prior to when a patient begins dialysis.

The indicator for whether a facility has a nearby rival may also be endogenous as market structure

Table 5: Determinants of Quality, First Stage

Instruments	(3) Log(Patients)	(4) Log(Patients)	(5) Log(Patients)	(5) Log(PPS at Closest Rival)
Log(Predicted Patient Count)	0.264***	0.264***	0.217***	0.028***
	(0.015)	(0.015)	(0.019)	(0.008)
log(Predicted Patients at Closest Rival)			0.056***	0.184***
			(0.012)	(0.010)
Year FE	Yes	Yes	Yes	Yes
Chain FE	No	No	Yes	Yes
Additional Controls	No	No	Yes	Yes
R-squared	0.636	0.636	0.686	0.526
F-statistic	3003.22	1999.81	760.58	5010.05
Observations	44435	44435	44435	44435

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

is likely determined by unobserved factors. This is a major challenge of industrial organization and is a motivating factor for my structural model for entry—to account for the nonrandom nature of market structure.

Table 6 contains the estimated results for five versions of equation 2, using the risk adjusted survival rate as a dependent variable. The first column regresses quality on the log of the number of patients treated at each facility, controlling only for year fixed effects. The negative coefficient is suggestive of a quantity-quality tradeoff. Column 2 adds a control for facility size and further confirms this result—given a fixed number of patients, expected survival improves as dialysis capacity increases. It should be noted that facility size, as measured by the count of dialysis stations, may also be endogenous. Productive or high quality facilities may invest in more dialysis stations relative to low quality facilities if they expect to be more likely to be able to utilize those machines. Due to these endogeneity concerns, it will be important to incorporate this capacity decision into the structural model.

Column 3 implements the IV described previously. This reveals a larger (and still negative) coefficient on patient caseload size. This is in line with the expectation that reverse causality from patient allocation may have been biasing this coefficient up in the OLS specifications. Column 4 adds an indicator for whether the facility had a rival within 10 miles and column 5 includes a richer set of controls such as chain fixed effects and facility age. The results in both of these columns suggest that having a nearby rival is associated with an improvement in the risk-adjusted survival rate of 0.7 to 1.1 percentage points.

The results for equation 2 estimated using additional risk adjusted outcomes are displayed in Table 7. They tell a very similar story to column 5 from Table 6. A doubling of the number of patients a facility treats leads to the average patient being hospitalized 0.063 more times in any given year, being one percentage point more likely to be hospitalized for septicemia, and a 1.3 percentage point decrease in the likelihood that

Table 6: Determinants of Quality, Survival

Dep. Var.: Risk Adj. Survival Rate	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Log(Patients)	-0.006***	-0.011***	-0.025***	-0.017***	-0.012***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Log(Stations)		0.010***	0.033***	0.025***	0.019***
		(0.002)	(0.005)	(0.005)	(0.004)
Has a Rival Within 10 miles				0.007***	0.011***
				(0.002)	(0.003)
Log(PPS at Closest Rival)					-0.004**
					(0.002)
Log(Patients with Private Insurance)					0.007***
					(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes
Chain FE	No	No	No	No	Yes
Additional Controls	No	No	No	No	Yes
R-squared	0.032	0.034	0.018	0.038	0.082
Observations	44435	44435	44435	44435	44435

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

any given treatment meets the URR dialysis adequacy standard. However, each of these effects is offset by increases in the number of dialysis stations a facility has. Additionally, having a nearby rival is associated with nontrivial improvements in these risk-adjusted outcomes. Having a nearby rival is associated with an average of 0.121 fewer hospitalizations for each patient in a given year, a 1.2 percentage point decrease in the likelihood of septicemia, and a 1.2 percentage point improvement in the dialysis adequacy rate.

In Table 7 I also display two additional selected variables: the log of patients per station at the closest rival and the log of patients with private insurance. Patients per station at the closest rival may help control for the effect that congestion at a nearby rival facility may have on the competitive effect. Congestion at a rival facility may make it less substitutable with facility j and less appealing as this congestion is likely related to worse outcomes and other externalities for patients. The results are consistent with congestion at a rival facility diminishing the competitive effect of that facility. To address the endogeneity of rival congestion I use an instrumental variable based on predicted patient counts at the rival, similar to how I previously instrumented for patient counts. Finally, the number of patients with private insurance seem to be correlated with better outcomes, unlike the correlation we see between overall patient counts and outcomes. This may be through selection—privately insured patients are more responsive to clinical quality—or treatment—privately insured patients pay more so the facilities they frequent have more resources.

Table 7: Determinants of Quality, Other Outcomes

	(1) Risk Adj. Survival IV	(2) Risk Adj. Hosp. IV	(3) Risk Adj. Infections IV	(4) Risk Adj. URR IV
Log(Patients)	-0.014***	0.063**	0.010***	-0.013***
	(0.003)	(0.021)	(0.002)	(0.004)
Log(Stations)	0.024***	-0.069**	-0.009***	0.009**
	(0.004)	(0.026)	(0.003)	(0.003)
Has a Rival Within 10 miles	0.019***	-0.121***	-0.012***	0.012*
	(0.004)	(0.031)	(0.003)	(0.005)
Log(PPS at Closest Rival)	-0.006**	0.034**	0.001	-0.005*
	(0.002)	(0.013)	(0.001)	(0.002)
Log(Patients with Private Insurance)	0.007***	-0.053***	-0.004***	0.007***
	(0.001)	(0.006)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
R-squared	0.079	0.085	0.060	0.198
Observations	44435	44429	44427	44382

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Entry and Payer Mix

These results consistently suggest that the realized market structure substantially influences clinical quality outcomes. Congestion may be detrimental to clinical quality while competition may serve to improve outcomes, though this effect may be limited to providers with nearby rivals that have sufficiently low congestion. Each of these channels suggests that more entry would result in better clinical care for patients. Payer mix may affect entry and capacity investment. Firms with profit motives will be more likely to enter in locations with more generous payers. To test this theory, albeit descriptively, I regress CBSA-level measures of entry and capacity on measures of payer mix. The results are in Table 8. Columns 1 through 4 show that the count of privately insured patients has a much larger influence on the number of facilities and dialysis stations than the count of Medicare patients. Columns 5 and 6 show that the percent of patients with private insurance is inversely related to the ratio of patients per station in each market. While these results should not be causally interpreted they show clear evidence that markets with more patients with private insurance also have more entry and capacity investment. I will seek to exploit the geographic distribution of patients of different payer types to estimate a model of market structure and quality provision.

Table 8: Market Entry and Payer Mix

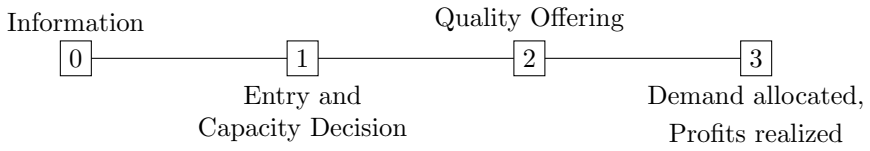
	(1) Facilities	(2) Facilities	(3) Dialysis Stations	(4) Dialysis Stations	(5) Patients per Station	(6) Patients per Station
Number of Medicare Patients	0.010***	0.016***	0.236***	0.261**		
	(0.002)	(0.003)	(0.024)	(0.085)		
Number of Privately Insured Patients	0.069***	0.078***	0.751**	1.852***		
	(0.019)	(0.017)	(0.286)	(0.407)		
Private Insurance Share					-0.858**	-0.599
					(0.295)	(0.508)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	No	Yes	No	Yes	No	Yes
R-squared	0.966	0.994	0.976	0.994	0.005	0.645
Observations	6886	6886	6886	6886	6886	6886

Standard errors clustered at market level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Model

In this section I present a structural model of entry, capacity, and quality competition. This model incorporates competitive interactions between firms and describes a causal relationship between exogenous state variables and market outcomes. It explicitly links the distribution of quality offering to market structure by allowing market structure to influence the expected return on quality. The timing of this model is described in figure 3. In the first stage potential entrants simultaneously decide whether or not to enter and how much capacity to build. In the second stage entrants choose a quality offering with full knowledge of the realized entry and capacity of their rivals. Finally, demand is allocated and profits are realized.

Figure 3: Timing



A few key elements of the model highlight the relationship between the financial incentives of dialysis providers and how they choose their product offering. First, competition has a spatial element. Providers and patients are differentiated by location. Patients will sort to dialysis facilities by making tradeoffs between travel costs and facility attributes, such as clinical quality. Thus the locations of potential entrants and patients are important state variables. Second, patients have different insurance types which pay dramatically different amounts for dialysis. This will result in entry probabilities that differ between locations close to more private insurance representation and areas with less. Third, entry decisions are made with incomplete

information about rivals. This allows for the possibility of ex-post entry regret. Fourth, when facilities choose a capacity level it affects profits in three ways: By increasing the fixed cost of entry, by directly affecting how many patients a facility treats, and by changing the marginal cost of quality. In all, variation in market structure will come from three sources: the distribution of patients and their payer-types, the distribution of potential entrants, and the random component of each firm's profitability. On the one hand, potential entrants located in areas with high patient density may be more likely to enter at high capacity levels. On the other hand, rival entrants will also be more likely to enter close to these locations. An entrant's profitability decreases with the entry of a rival for two reasons. The first is business stealing. Second, variable costs may go up if the entrant is forced to improve its quality in order to retain demand. These will push down the likelihood of entry in these areas.

In this game firms choose their strategies with incomplete information about the profitability of rival firms. These strategies will depend on payoff relevant state variables. These state variables comprise of the set of potential entrants, $\mathcal{F}$, the set of dialysis patients $\mathcal{P}$, and their exogenous characteristics (location, chain, payer type, etc). I denote the set of states as $\mathcal{X} = (\mathcal{F}, \mathcal{P})$. Given these, firm strategies comprise a Sequential Bayesian Nash Equilibrium that is simultaneously characterized by capacity choice probabilities (zero indicating no entry), a policy function for quality, and patient choice probabilities. The patient choice probabilities must form a Bayesian Nash Equilibrium of a subgame in which the patients sort across facilities. Since congestion enters into the utility function, each patient's decision on where to go affects the utility of other patients. In equilibrium, patient choice probabilities will maximize the expected utility for each patient, given the choice probabilities of all other patients. On the supply side, a policy function maps the set of rival entrants to the profit maximizing quality offering for each provider, taking into account the quality of rivals and the resulting patient choice probabilities. Finally, the equilibrium entry probabilities maximize expected profits for potential entrants, taking into account the beliefs about rival entry probabilities (which, in equilibrium will be the same as those rivals' strategies), the policy function, and how patients will sort across facilities.

This model captures many important aspects of competition in this industry but abstracts from some others. First, in this model each dialysis facility acts as an independent firm. In reality most facilities are owned and operated by corporations that may coordinate capacity investment decisions across facilities. Second, dialysis providers are strictly profit maximizers. In reality, 78% of facilities are for-profit. Third, private insurance payment is exogenous[23] Another simplification that I make is that I endogenize a limited set of quality dimensions. While I capture two important dimensions of quality competition, there are

[23]Generally, private insurance rates are the result of bargaining between provider and insurance company. Market concentration is likely a contributor to bargaining power on the provider side (Cutler et al., 2015).

other aspects of quality that are probably strategically chosen. Fifth, I assume that demand for dialysis is fixed—patients do not opt out of or into dialysis. They can opt in or out of in-center dialysis but not in or out of dialysis altogether. Under this assumption providers cannot effect aggregate demand by providing better service to keep patients alive or by allowing patients to initiate dialysis sooner. Finally, I assume that insurance type is exogenous—that who gets private insurance does not vary by provider.[24]

In this game firms strategically pick their profit maximizing strategy by forming expectations through backwards induction. Following this I discuss each stage of the model beginning with demand and followed by the quality decision stage and the entry stage.

5.1 Demand

Following McFadden (1973) I use a discrete choice model to estimate patient utility functions. On the demand side, the decision making unit is likely some composite of patient, a referring physician, and the dialysis provider being chosen. I present this model, however, as if it is the patient making the decision. This simplification relies on two assumptions. The first is that patients and referring physicians have aligned objectives. The second assumption is that dialysis facilities do not turn away patients in any systematic way.

Patient i has a choice set, $\mathcal{J}_i = \{0, 1, ...J_i\}$, which is comprised of J_i dialysis facilities and the outside option (0), home dialysis. Patient i chooses the utility maximizing facility from their choice set. The indirect utility received by patient i for choosing option j is:

$$u_{ij} = \begin{cases} g(d_{ij}, I_i) + \Gamma(I_i)H_j + \lambda(I_i)X_j + \xi_j + \varepsilon_{ij} & \text{if } j \neq 0 \\ \varepsilon_{i0} & otherwise \end{cases} \tag{3}$$

This function allows utility to depend on facility characteristics, such as location, clinical quality, congestion, and facility size, in a way that varies by patient types. Patient preferences may vary based on where the patient lives, what kind of insurance the patient has, and whether or not the patient was employed when initiating dialysis. The first term, $g(.)$, expresses the disutility from travel incurred by patients. I allow this to vary by insurance type and employment status. People with private insurance or who are employed may have different location preferences because are more mobile, must choose in-network providers, or prefer a dialysis facility close to where they work.

The second term captures utility to patients from endogenous variables, including clinical quality ($\mathcal{Q}_j$), congestion ($\mathcal{C}$) and facility size or capacity (k_j). $H_j = [\mathcal{Q}_j, \mathcal{C}, k_j]$ denotes the set of endogenous attributes for facility j. I proxy for clinical quality, $\mathcal{Q}$, using each facility's risk adjusted survival rate. While patients may

[24] In recent years this assumption appears problematic but in the years covered by my sample it is relatively weak.

value many aspects of clinical quality I view this as a sufficient statistic for a facility's clinical quality. The model is agnostic in how patients evaluate or learn about quality. It is possible that knowledge of a clinic's quality is incorporated into the decision through the referring physician.[25] To measure congestion, $\mathcal{C}$, I use the ratio of hemodialysis patients to dialysis stations. This term captures a conflation of mechanisms that may deter patients from choosing a facility. These include the possibility that facility j undergoes a stock-out ans is simply removed from the choice set, as well as disutility from choosing a crowded facility (scheduling challenges, wait times, etc). Similarly, X_j contains a vector of exogenous facility characteristics such as for-profit status and chain-affiliation. I allow utility for both the endogenous and exogenous attributes to vary by patient characteristics.

The term ξ_j captures utility from facility j's "unobserved amenities." These include facility characteristics that affect the utility of all patients in the same way. These may be things such as proximity to an interstate on-ramp, having nicer televisions, massage chairs, etc.

Finally, a vector of constants, λ, interacted with patient characteristics is included to normalize the utility differences between in-center treatment and the outside option—home dialysis. This normalization is allowed to vary by patient type to capture the fact that patients who are working, have better health, or higher incomes, may be more likely to choose home treatment. The outside option is normalized to have zero expected utility.

Assuming a multinomial logit model, facilities form expectations for their caseloads that have the familiar form:

$$\begin{aligned} S_j &= \sum_i \frac{\exp(g(d_{ij}, I_i) + \Gamma(I_i)H_j + \lambda(I_i)X_j + \xi_j)}{\sum_{j'} \exp(g(d_{ij'}, I_i) + \Gamma(I_i)H_{j'} + \lambda(I_i)X_{j'} + \xi_{j'}} \\ &= \sum_i s_{ij}(\tilde{\mathcal{X}}, H) \end{aligned} \tag{4}$$

Provider caseloads, shown in 4 depend on state variables as well as the endogenous variables—quality, congestion and capacity. I use the notation $\tilde{\mathcal{X}}$ to denote the post-entry states. I denote these $\tilde{\mathcal{X}} = (\tilde{\mathcal{F}}, \mathcal{P})$, where $\tilde{\mathcal{F}}$ is the set of entrants and their characteristics and $\mathcal{P}$ is the same set of patients as was used in the ex-ante states, $\mathcal{X}$. A provider's expected caseload depends on capacity and quality decisions as well as the choice probabilities of other patients. Since H contains the congestion attribute, in equilibrium patients will have a set of choice probabilities from which they cannot optimally deviate, given the set of choice probabilities of other patients. This highlights the sorting aspect of this part of the model.

[25] In discussions with nephrologists, who refer patients to kidney dialysis, they expressed that while they were unlikely to refer a patient to a facility only because of good clinical quality they were likely to warn patients about facilities with reputations of poor quality.

5.2 Quality Decision

In the second stage of the model, entry has been realized and capacity decisions are known to all providers, just as it was in the demand stage. I also assume providers know the distribution of demand and patient preferences. Given these, entering providers pick the quality level that will maximize expected profits. Specifically, I allow providers to affect their risk adjusted survival rate. In reality, they do not have direct control over survival, but it may serve as a summary statistic for all of the activities a provider does that do affect outcomes. At this stage all attributes other than quality and congestion are fixed. The objective function at this stage is:

$$\max_{\mathcal{Q}_j \in [0,\bar{\mathcal{Q}}]} \sum_i \Big(P_i - VC_j(.)\Big) s_{ij}(\tilde{\mathcal{X}}, H). \tag{5}$$

In this equation, P_i is the expected payment per treatment from patient i's payer and VC is the variable cost function, which is assumed to be constant within a facility.

One component governing the equilibrium distribution of quality offering is the variable cost function. I allow variable costs to depend on product attributes such as quality and congestion. Providers can improve quality by expending more on inputs such as labor and dialyzers. Variable costs may also vary by the level of utilization of capital (patients per station). I use the following parameterization for variable costs:

$$VC_j(\mathcal{Q}_j, \mathcal{C}_j) = c_0 + c_1\mathcal{Q}_j + c_2\mathcal{Q}_j^2 + c_3\mathcal{C}_j + c_4\mathcal{C}_j * \mathcal{Q}_j \tag{6}$$

The interaction term allows the cost of quality to vary by facility congestion. Providers facing high congestion can still provide quality but at a potentially increasing cost as it requires things such as extended hours, better scheduling, more costly materials, etc. Including the congestion terms also ties capacity investment decisions, made in the first stage, to the second stage quality decision. If c_3 and c_4 are positive and holding caseload constant, building more dialysis machines will lower both variable costs and the marginal cost of quality.

The policy function is a mapping from the post-entry states to a vector of quality offerings that maximize profits. Formally, $\vec{\mathcal{Q}}^* = \vec{\mathcal{Q}}^*(\tilde{\mathcal{X}})$. The quality decision is made with complete information, that is, with a knowledge of which potential entrants entered and what capacity decisions they made, it relies on a set of ex-post entry states. Existence of $\vec{\mathcal{Q}}^*$ follows from the convexity of shares (equation 4) and the variable cost function. The solution to $\vec{\mathcal{Q}}^*$ is conceptually similar to Bertrand competition except in this case providers are choosing quality, rather than price, and quality affects both demand and, potentially, cost.

Profits will be maximized at the quality level that satisfies the first order conditions in equation 7,

equating marginal revenues and marginal costs. The quality offerings that solve this equation form the Nash equilibrium quality levels. Marginal costs have two components. The first shows that costs increase in quality because the expected number of patients treated increases. The second shows that variable costs themselves change with quality. This highlights the assumption that all patients are treated to the same quality level and have the same costs—as quality goes up, variable costs for all patients go up.[26]

$$\underbrace{\sum_i P_i \frac{\partial s_{ij}}{\partial \mathcal{Q}_j}}_{\text{Marginal Revenues}} = \underbrace{\sum_i \left(VC(\mathcal{Q}_j, \mathcal{C}_j) \frac{\partial s_{ij}}{\partial \mathcal{Q}_j} + \frac{\partial VC}{\partial \mathcal{Q}_j}(\mathcal{Q}_j, \mathcal{C}_j) s_{ij} \right)}_{\text{Marginal Cost of Quality}} \tag{7}$$

Marginal revenues are determined by the distribution of patients, their preferences, and the generosity of payers, as well as providers and their attributes. It is the heterogeneity of preferences that allows the model to predict a nondegenerate distribution of quality. For example, a facility that is geographically convenient for lots of patients may have lower marginal revenues from increasing quality and, therefore, may provide lower quality levels. Higher marginal revenues for facilities situated in the vicinity of privately insured patients may induce those facilities to offer higher quality levels.

This part of the model highlights various mechanisms that may be useful in spurring higher clinical quality, even holding the extensive margin fixed. Increasing marginal revenues by increasing P_i will incentivize higher quality by shifting marginal revenues up. If patients, who value clinical quality, pay more then providers will compete to offer higher clinical quality. If the variable cost function could be manipulated it similarly could be used to intensify quality competition. Finally, the elasticities of demand could also be manipulated to alter the equilibrium quality offering. This could potentially be done through interventions such as travel subsidies or, possibly, though information dissemination programs that may affect how much patients value clinical quality. Each of these possible policy interventions, however, would likely change dialysis supply which would change patients' choices sets and work into the equilibrium quality offering through the elasticities. To fully understand these quality decisions and how to best influence them we must turn our attention to the extensive margin.

5.3 Entry

In the first stage, firms with incomplete information decide whether or not to enter and how much capacity to provide. Ultimately each firm's payoff will depend on the state variables, its own actions, and the actions of others. However, in the incomplete information environment firms do not know the actions of their rivals and must form strategies based on expectations over their rivals' actions.

[26] The assumption that all patients cost the same to treat could easily be relaxed.

Two opposing factors create a tension that shapes the optimal entry strategies. On the one hand, a firm's own revenues at the end of the game increase in capacity. More capacity creates more availability and it decreases the cost of clinical quality. On the other hand, the payoffs from capacity decrease in the capacity of rival facilities. Ex post, a firm with a large rival may be better off saving on fixed costs and bringing only a small amount of capacity to market. However, when firms make their entry and capacity decisions they do not know the actions of their rivals. Instead, they form expectations over their rivals entry and capacity decisions and choose a strategy that maximizes their expected profits. Thus this model allows for ex-post regret on the entry margin.

Each potential entrant considers a set of capacity levels, $\mathcal{K} = \{0, 1, ..., K\}$, where 0 indicates that they do not enter. For each capacity level they draw a random profitability shock, ε_j^k, which is private knowledge. Firms do know the distribution of shocks for their rival potential entrants. Upon entry, firm j choosing capacity k will realize ex-post profits:

$$\pi_j(k; \tilde{\mathcal{S}}) = \underbrace{\sum_i (P_i - VC(\mathcal{Q}_j^*(\tilde{\mathcal{S}}), \mathcal{C}_j^*(\tilde{\mathcal{S}})))s_{ij}(\tilde{\mathcal{S}}) - fc(k; X_j)}_{\bar{\pi}_j(k;\tilde{\mathcal{S}})} + \varepsilon_j^k. \tag{8}$$

The first term, the summation, represents revenues less the variable costs of treating patients to the ex-post profit maximizing quality level. The function $fc(.)$ is the fixed costs associated with entering with capacity k.

Since potential entrants do not know their rivals' profitability shocks, they form expectations over those shocks:

$$\mathbb{E}[\pi_j(k; \mathcal{S})] = \begin{cases} \int_\varepsilon \bar{\pi}_j(k; \tilde{\mathcal{S}}) + \varepsilon_j^k & \text{if } k > 0 \\ \varepsilon_j^0 & \text{if } k = 0. \end{cases} \tag{9}$$

Their objective is then to choose k to maximize expected profits.[27] I addition to assuming the εs are private information, I assume they are independent. With this assumption the unobserved portion of profitability is identically distributed across firms, meaning that differences in firms entry probabilities will come only from observable shifter of profit (such as location). Since these are common knowledge, all firms will have the same expectations for the probability of each rivals entry decision.

[27] This model, as specified, assumes that strategic decisions are made at the facility level and that there is not coordination across facilities. This is a strong assumption since the majority of facilities are owned and operated by two chains. Relaxing this assumption is left for future work.

6 Estimation

I estimate the structural model in three steps. First, i estimate the preference parameters from the demand model. The resulting demand elasticities govern the financial incentives facing dialysis providers and will in turn be used to back out their costs. In a second step, I estimate the variable costs of providing dialysis. These, together with prices and demand elasticities describe the payoffs from entering the market. In a third step I combine them together with observed entry patterns to estimate fixed costs that rationalize entry.

6.1 Demand

I estimate equation 3 using a two-stage procedure. In the first stage I use a multinomial logit model to estimate the modified version of equation 3:

$$u_{ij} = \delta_j + g(d_i j, I_i) + \Gamma(I_i)H_j + \lambda(I_i)X_j + \varepsilon_{ij}. \tag{10}$$

The mean utility, δ_j, represents the utility from facility j that is common all patients. This mean utility is modified to specific patients based on their location and the patient characteristics included in I_i. Since there is a δ_j for every facility, this creates a high-dimensional computational burden which I address by using a contraction mapping approach similar to Berry (1994). This approach is built into a maximum likelihood estimation framework. In an outer loop, maximum likelihood is used to estimate the patient-specific parameters ($g()$, $\Gamma(I_i)$, and $\lambda(I_i)$). For each iteration of this procedure a contraction mapping finds the values of δ_j that matches the predicted facility market shares to the observed shares.

I parameterize $g()$ by making it a quadratic function of distance and interacting each term with a constant, an indicator for whether the patient has private insurance, and an indicator for whether the patient was employed at dialysis initiation. I interact this vector of patient characteristics with facility quality, congestion, and the constant normalizing utility from the outside option. This allows me to observe how patients of different types reveal different preferences.

In the second stage, the δ_j's are decomposed by projecting them onto facility attributes and recovering the structural error term. This is done using a regression framework to estimate the following equation:

$$\delta_j = \beta_1 H_j + \beta_2 X_j + \xi_j \tag{11}$$

The ξ_j's are recovered and interpreted as an unobserved attribute that contribute to the mean utility of all patients who choose facility j. In this second stage I address the endogeneity of congestion by using

two-stage least squares, rather than OLS. As instruments, I use predicted counts of Medicare patients and predicted counts of privately insured patients. This is analogous to my instrumental variables strategy in the reduced form section and relies on similar assumptions to satisfy the exclusion restrictions. One additional assumption using this identification strategy is that the endogenous variables are confined to the mean utilities.

I also include chain and market dummies in X_j. Chain dummies, which are similar to brand dummies, are useful for capturing unobserved factors related to utility and correlated with chain affiliation and will improve model fit. They will also help with identification by capturing the correlation between quality and the chain-specific mean of unobserved quality, even without an instrument (Nevo, 2000).

One final assumption I make is that choice sets are observable. I allow patients to go to any facility in their CBSA. CBSAs are rather large and are likely inclusive of facilities that may not actually be considered by all patients in the CBSA. Inclusion of travel costs in the specification will make the choice of these distant facilities a low probability. However, another concern about this choice set specification is that some facilities are likely capacity constrained and may not be in a patient's choice set. This unobservability of patient choice sets may bias the estimates of other attributes toward zero. In my specification this concern is largely assuaged by the inclusion of the congestion term. While capacity-constrained status is unobservable to the econometrician, it is correlated with the number of patients per station at each facility. Facilities with lots of patients per station are more likely to behave in a constrained manner by turning away patients, compared to facilities with fewer patients. The congestion term will pick up on this and largely correct for the unobservable capacity-constrained status.

6.2 Variable Costs

With the demand estimates in hand, I estimate the variable cost function. I do this using GMM and matching the observed quality distribution with the quality distribution predicted by the policy function. The policy function maps from states to the distribution of quality that satisfies the firms' first order conditions (equation 7). I use the FOCs to form a fixed point contraction mapping:

$$\mathcal{Q}* = f(\mathcal{Q}^*, \mathcal{C}^*(\mathcal{Q}^*), \tilde{\mathcal{S}}; c). \tag{12}$$

To solve for $\mathcal{Q}^*$ in equation 12 I use the following algorithm:

1. Pick an initial guess at $\mathcal{Q}$. Call it $\mathcal{Q}^0$.
2. Solve for $\mathcal{C}^*(\mathcal{Q}^0)$

(a) Compute $S_j(\mathcal{Q}^0, \mathcal{C}^0(\mathcal{Q}^0))$

(b) Compute $\mathcal{C}^1(\mathcal{Q}^0) = \frac{S_j}{k_j}$

(c) Compute $S_j(\mathcal{Q}^0, \mathcal{C}^1(\mathcal{Q}^0))$

(d) Repeat b-c until $\mathcal{C}^*(\mathcal{Q}^0)$ converges

3. Compute $\mathcal{Q}^1 = f(\mathcal{Q}^0, \mathcal{C}^*(\mathcal{Q}^0), \tilde{\mathcal{S}}; c)$

4. Repeat 2-3 until $\mathcal{Q}$ converges to $\mathcal{Q}^*$.

The GMM objective function is:

$$\min_c (\mathcal{Q}^*(\tilde{\mathcal{S}}; c) - \mathcal{Q})'(\mathcal{Q}^*(\tilde{\mathcal{S}}; c) - \mathcal{Q}) \tag{13}$$

I find the estimates of c that minimize (13).

6.3 Entry Game

In a final step entry costs are estimated via maximum likelihood. To complete this step I close off the model with two additional assumptions: a functional form for entry costs and a distributional assumption on the potential entrants' choice shocks. Since potential entrants are profit maximizers the structural profit function governs the payoffs to firm strategies (see equation 8). I assume that entry costs have the following functional form:

$$fc(k_j, X_j; \phi) = \phi_0(X_j) + \phi_1(X_j)k_j + \phi_2 \text{Density} + \phi_3 \text{Density} * k_j + \varepsilon_j^k. \tag{14}$$

Here, X_j includes exogenous characteristics of the potential entrant such as chain-affiliation and for-profit status. This functional form frames entry costs as having three components: a fixed cost that is constant across all capacity choices ($\phi_0(X_j)$), a component that increases in size ($\phi_1(X_j)k_j$), and a component consisting of attributes of the specific location being considered. I allow the first two components to vary by potential entrant attribute. For example, DaVita and Fresenius may face different capital costs because Fresenius is vertically integrated and makes their own dialysis machines. By including year and CBSA fixed effects I can capture unobserved heterogeneity at the market and year levels.

I also assume that the choice shocks, ε_j^k, are distributed i.i.d. Type I Extreme Value. This assumption

provides a closed form on each player's choice probabilities. The expected choice probabilities of firm j are:

$$\begin{aligned}
\mathbb{P}_j(k=0;\phi) &= \frac{1}{\sum_{k'\in\mathcal{K}} \exp\left(\mathbb{E}[\bar{\pi}_j(k';\tilde{\mathcal{S}})]\right)} \\
\mathbb{P}_j(k=1;\phi) &= \frac{\exp\left(\mathbb{E}[\bar{\pi}_j(1;\tilde{\mathcal{S}})]\right)}{\sum_{k'\in\mathcal{K}} \exp\left(\mathbb{E}[\bar{\pi}_j(k';\tilde{\mathcal{S}})]\right)} \\
&\ldots \\
\mathbb{P}_j(k=K;\phi) &= \frac{\exp\left(\mathbb{E}[\bar{\pi}_j(K;\tilde{\mathcal{S}})]\right)}{\sum_{k'\in\mathcal{K}} \exp\left(\mathbb{E}[\bar{\pi}_j(k';\tilde{\mathcal{S}})]\right)}.
\end{aligned} \tag{15}$$

These choice probabilities are the ex-ante entry probabilities for any potential entrant before realizing their choice shocks. Expected profits have the form:

$$\mathbb{E}[\bar{\pi}_j(k';\tilde{\mathcal{S}})] = \int_{\tilde{\mathcal{S}}} \bar{\pi}_j(k';\tilde{\mathcal{S}})\mathbb{P}(\tilde{\mathcal{S}}), \tag{16}$$

where the integral is taken over all possible ex-post states for which firm j entered with capacity level k'. Due to the size of firms' choice sets and the number of potential entrants, I use simulation to approximate the integral. The choice probabilities form the basis for the likelihood function, which is maximized over the remaining unknown parameters—those governing entry costs.

There are potentially two ways to compute the equilibrium choice probabilities. The first, attributed to Rust (1987), uses a fixed point to fully solve the choice probabilities for each parameter guess. Due to the large number of potential entrants, the burden of solving the nested fixed points involved in quality competition and patient sorting, firm heterogeneity, and the large choice sets, this full solution method is infeasible.

Instead, I use a two-step approach adapted from Hotz and Miller (1993).[28] The first step consists of semi-parametrically recovering choice probabilities. These choice probabilities are then used as the players' beliefs about rival strategies to construct the expected payoffs from each of their potential choices. This by-passes fully solving the fixed-point in order to relieve the computational burden of estimation.

I treat CBSAs as isolated markets and construct a set of potential entrants so that there are twice as many potential entrants as realized entrants within the CBSA. I randomly assign each non-entrant location to a ZIP code centroid within the CBSA. The remaining exogenous attributes (chain affiliation, for-profit status, and the unobserved attribute) are drawn randomly. In the first step of the estimation process, I use a multinomial logit model where the choice variable is the capacity level they may enter at, where zero indicates they did not enter. I use this to estimate the probability of each choice as a function of exogenous

[28] While there initial application was in a dynamic setting, I adapt it to a static setting due to the high-dimensionality of the problem at hand.

state variables, including the number of patients withing various distance bands around a potential entrant's location, population, population density, population over 65, median income, etc., all fully interacted.

7 Results

7.1 Demand Estimates

Parameter estimates of the demand model are found in Tables 9 and 10. Table 9 contains the estimates from the first stage—parameters describing how preferences differ for patients of different types. Table 10 contains the estimates from the second stage—how facility attributes contribute to utility in a way that is common for all patients. Because of the absence of prices, the magnitudes of these estimates should be interpreted with respect to travel costs. I also provide a table with selected elasticities below (table 11).

The first stage estimates reveal baseline travel costs that are concave. Patients who are employed seem to have lower travel costs. These patients are likely to be healthier, more financially secure, and more mobile. Patients with private insurance demonstrate stronger preferences for clinical quality and are more affected by congestion, as demonstrated by the negative sign on the interaction of congestion and private insurance. If privately insured patients were more likely to be accepted at a facility that is close to being constrained this would suggest a positive coefficient on this interaction. While this may be happening, since the estimate is negative we can infer that privately insured patients avoid congested facilities and this more than offsets a potential stock out effect. The outside option also appears relatively more appealing to privately insured and employed patients. Patients who work, are more confident in their adherence, and have higher opportunity costs of time are more likely to choose home dialysis. The negative signs on these coefficients show that the outside option is relatively appealing to privately insured patients and employed patients.

The second stage results decompose the mean utility from facility attributes. The endogeneity issue with congestion is apparent here. Using the OLS specification it looks like patients get utility from congestion. In reality facilities are probably congested for unobserved reasons that drive this result. When I employ two-stage least squares, it flips the sign on congestion and reveals strong disutility from crowded facilities. In addition, it changes the magnitudes of some of the other attributes, such as quality. One would expect this to happen if quality is correlated with the unobserved attributes driving the endogeneity of congestion.

Patients value clinical quality. The results show that they tend to be willing to travel about 1.3 additional miles for a one standard deviation improvement in clinical quality—an eight percentage point improvement in risk adjusted survival. Table 11 shows that a one percent increase in facility quality is rewarded with a 0.85% increase in demand. In addition there is strong disutility from congestion and

Table 9: Demand Estimates, First Stage

	Coefficient	S.E.
Distance	-0.164***	(0.004)
Distance Squared	0.003***	(0.0002)
Distance*Pop. Density	-0.003***	(0.004)
Distance Squared*Pop. Density	-0.001***	(0.0004)
Dist*Private Insurance	-0.011	(0.021)
Dist. Sq.*Private Insurance	0.001	(0.001)
Dist*Employed	0.046***	(0.015)
Dist. Sq.*Employed	- 0.001	(0.001)
Quality*Private Insurance	1.171**	(0.402)
Quality*Employed	1.344***	(0.291)
Congestion*Private Insurance	-0.072***	(0.021)
Congestion*Employed	0.049***	(0.015)
Stations*Private Insurance	-0.006	(0.003)
Stations*Employed	0.004	(0.002)
Outside Option*Private Insurance	1.138***	(0.362)
Outside Option*Employed	1.817***	(0.261)

distance. Compared to Medicare patients, privately insured patients are more responsive to clinical quality and less responsive to travel costs and congestion.

Table 10: Second Stage of Demand Estimation: Decomposition of Mean Utility

	OLS	2SLS
Quality	0.144	2.411***
	(0.245)	(0.667)
Congestion (Patients per station)	0.331***	-0.152***
	(0.017)	(0.032)
Number of Dialysis Stations	0.025***	-0.027
	(0.003)	(0.017)
For-profit	0.067	-0.331
	(0.057)	(0.176)
Outside Option	-0.392	-1.043***
	(0.219)	(0.021)
Chain Dummies	X	X
Market*Year FEs	X	X

Table 11: Mean Elasticities of Demand

	All Patients	Medicare Patients	Privately Insured Patients
Distance	-0.240	-0.240	-0.230
Quality	0.850	0.800	1.433
Congestion	-0.135	-0.127	-0.233

7.2 Variable Costs

The variable cost estimates decompose the estimated cost of dialysis into attributes. The estimates show that variable costs increase quadratically in the risk adjusted survival rate. Additionally, the marginal cost of quality increases in congestion. The estimates suggest an average cost of a single treatment of $183, and a markup of $13.21. Additionally, the cost of improving the risk adjusted survival rate by one percentage point is $330.24 per patient per year. This would reduce the average markup by over $2. For the average facility this works out to around $21,000 per year.

Table 12: Variable Costs

	Estimates ($1000s per Year)
Constant	0.08
	(0.034)
Quality	0.01
	(0.022)
Quality^2	14.93
	(1.092)
Congestion	2.12
	(0.223)
Congestion*Quality	5.69
	(0.117)
Stations	0.14
	(0.211)
Stations*Quality	-0.64
	(0.212)
Chain Interactions	Yes

7.3 Fixed Costs

The fixed cost estimates are displayed in Table 13. Fixed costs increase in the number of stations and are smaller for chains than independent facilities. This suggests that chains have lower entry costs and are somehow better at scaling up dialysis facilities. Interestingly, the cost per station for Fresenius is smaller than the cost per station for DaVita. Fresenius is a vertically integrated company in that is makes its own dialysis stations. This seems to be advantageous for them as it may results in lower fixed costs. Additionally, fixed costs increase with the population density of the location, likely reflecting real estate costs.

Table 13: Fixed Costs

	Estimates, in Dollars
Constant	253,558.60
	(10,877)
Stations	42,440.05
	(15,117)
Log(Pop Density)	5,521.91
	(599)
DaVita	-6,550.62
	(748)
DaVita*Stations	-1,238.32
	(331)
Fresenius	-4,353.21
	(824)
Fresenius*Stations	-4,011.54
	(831)
Other Chain	-1,012.23
	(902)
Other Chain*Stations	-1,173
	(785)
Year Dummies	X

7.4 Goodness of Fit

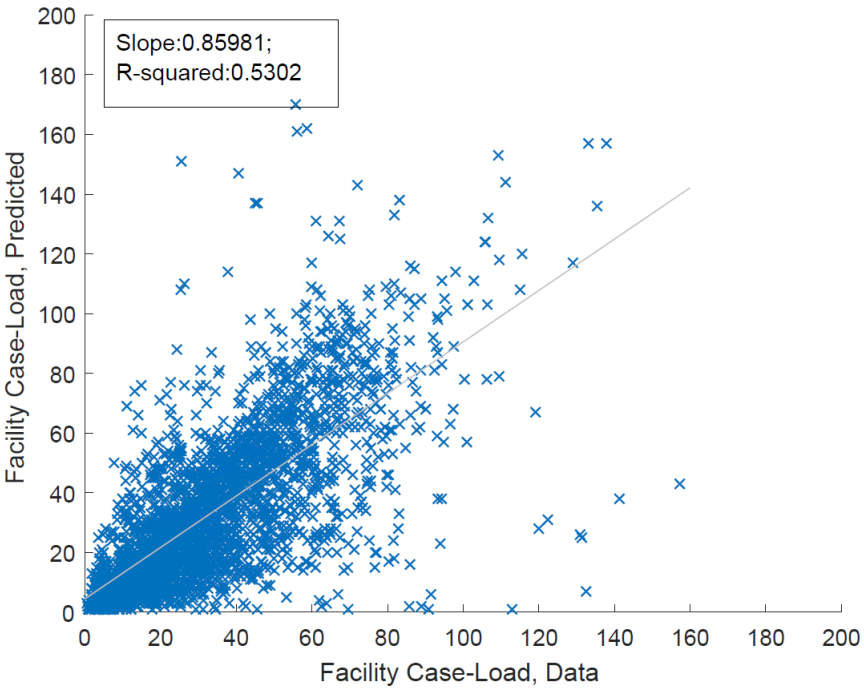
I use a form of out-of-sample validation to demonstrate the goodness-of-fit of the structural model. The idea is to compare the outcomes predicted by the model estimates to the realized outcomes for a subset of data that were not used to estimate the model. This comparison will lend credibility to the model predictions if they match reasonably well. I make two types of comparisons between the observed data and the model predictions. First, in Figure 4 I demonstrate the performance of the front-end of the model. This applies the quality policy function and demand model to the realized market structure in the excluded sample, and compares the predicted facility patient counts and quality level with the realizations in the data. This

evaluates the performance of this part of the model, turning off the entry stage. Second, in Table 14 I correlations between market outcomes and key relationships within the data and the model predictions. This describes the extent to which the model successfully replicates key aspects of market structure and competition in this industry.

The first goodness of fit exercise shows that the model performs well in predicting facility shares. In particularly, the model predictions explain 53 percent of the variation in observed facility shares. The model does not perform as well when it comes to simulating clinical quality. However, the mean clinical quality prediction is very close to the observed mean. Additionally, the regression line of observed survival rates on predicted survival rates has a positive slope suggesting that it is capturing some of the heterogeneity.

In Table 14 the correlation coefficients suggest that the model does a good job of recreating the market structure in observed in the excluded sample. The correlation coefficient between expected number of entrants in a market and the observed number of entrants is 0.93. The corresponding correlation coefficient for the number of stations is 0.81. Additionally, the model does a decent job of reproducing moments from the market-level distribution of clinical quality. For example, the correlation coefficient for the observed market-level mean quality and the predicted market-level mean quality is 0.29. Overall, the model appears to be very predictive of market structure, clinical quality, and patient allocation in the excluded data.

Figure 4: Goodness of Fit I



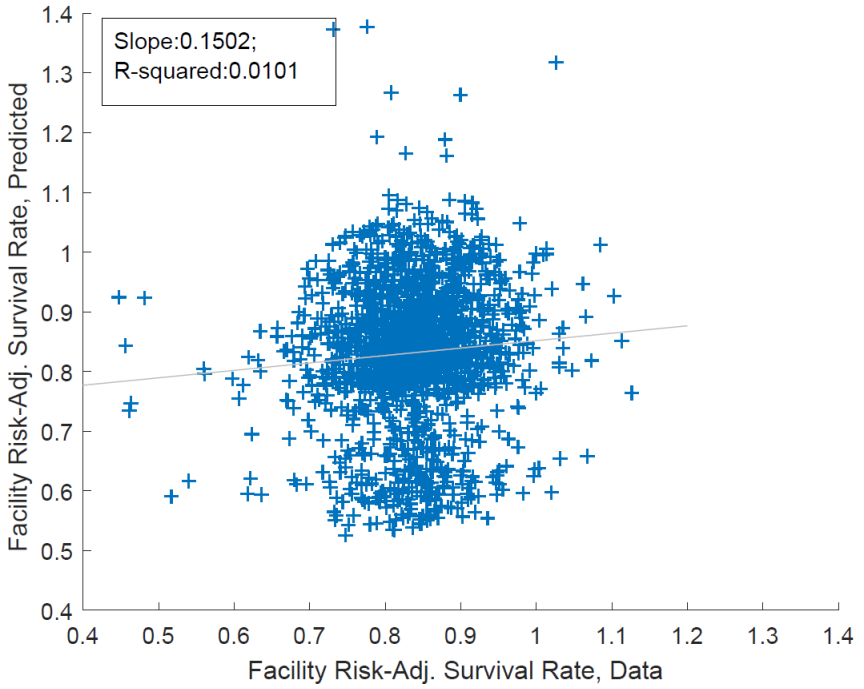


Table 14: Model Fit II

Market-Level Outcomes:		Correlation Coefficient Between Prediciton and Data
Number of Entrants		0.93
Number of Stations		0.81
Patients Per Facility		0.83
Patients Per Station		0.68
	Mean	0.29
Quality Distribution:	St. Dev.	0.23
	Range	0.21

	Correlation in Observed Data	Correlation in Predictions
Mean Quality and Patients per Station	-0.05	-0.10
Mean Quality and Private Insurance Share	0.09	0.04

*Correlation coefficients between facility characteristics in observed data and simulations.

8 Counterfactuals

I use the model estimates to simulate a variety of policy counterfactuals that explore the effect of price regulation on patient outcomes and how regulators can improve welfare and outcomes in this industry. These counterfacutals include changing the Medicare reimbursement rate, reducing the private insurance rate to be equal to the Medicare rate, subsidizing entry, and subsidizing travel. Each of these counterfactuals operate through different mechanisms to affect market structure, welfare and quality. In order to calculate consumer surplus I use values from Godavarthy et al. (2014) to construct estimated travel costs and monetize utility. For more details on how I do this, see Appendix Section G.

8.1 Changing Medicare Payment Rates

I first simulate a set of counterfactuals in which regulators change the Medicare reimbursement rate. Changing the reimbursement rate may affect patients in two ways. First, if the reimbursement rate is increased it will increase the per-patient markup and the returns to quality which may result in higher equilibrium quality. Second, it may induce additional entry or entry in different locations (since Medicare patients become more valuable relative to privately insured patients). This may also improve patient welfare, because more entry means less congestion and possibly closer options. However, the effect on quality is ambiguous. The quality elasticity of demand may actually decrease as providers compete more on other

margins such as capacity and location. The counterfactual simulations will show the average net effect.

The results detailed in Table 15 show how changing the reimbursement rate impacts entry, clinical quality, and welfare. Increasing the Medicare rate by 10 percent increases total capacity by 2.1 percent and improves the average risk adjusted survival rate by 0.9 percentage points, in equilibrium. This amounts to an estimated 3,622 additional life-years saved but these savings are costly—$357 thousand per life year.[29] The increase in the Medicare reimbursement rate cost more than the welfare it produces. The 10 percent increase in the reimbursement rate costs $1,292 million per year but only increases dollar-equivalent welfare by $700 million, 91% of which is captured by producers. One $65 million is passed through to consumers.

A proposed 100% increase in the Medicare rate has similar, though larger results. This counterfactual is similar to what would happen if Medicare raised its rates to the level of a typical private insurance plan. The result is more entry and capacity investment, improved clinical quality and consumer surplus, but once again, about 90% of the pass-through is captured by producers. In this setting, travel costs are important enough to patients that their demand is relatively inelastic and, consequently, producers are able to exploit their local market power to capture most of the pass through.

8.2 Reducing Private Insurance Rates to Medicare Rates

This counterfactual may speak to the implications of two proposed policies: One is a proposed cap on the rates dialysis facilities can charge to insurers, the other is Medicare for all—eliminating private insurance all together and switching those patients over to Medicare. The results show small decreases in entry and clinical quality, in addition to additional Medicare expenditures. However, it is difficult to evaluate the savings to commercial insurance plans.

8.3 Entry Subsidies

This section presents the counterfactual results for a policy intervention subsidizing entry. The purpose of this counterfacutal is two fold. First, it explores the cost-effectiveness of using entry subsidies to improve welfare and patient outcomes. Second, it highlights the relationship between the extensive margin and quality—that is, it will sign the effect of additional entry on quality. Recall that in the Medicare reimbursement rate counterfactual, providers adjusted their quality levels responding to two factors: a change in the per-patient markup and changes in supply-side capacity. In this counterfactual the markup will only change because variable costs are a function of congestion. The expected response of quality to additional entry is theoretically ambiguous. On the one hand, additional capacity will lower the average facility con-

[29] The quality-adjusted value of a statistical life year is $120 thousand (Lee et al., 2009).

Table 15: Counterfactual I, Change in Medicare Reimbursement Rate

Policies	Increase Medicare Rate 10%	Increase Medicare Rate 100%	Switch Private Insurance to Medicare	Subsidize 10% of Entry Costs
	Percent Change, Relative to Baseline			
Number of Entrants	2.0	14.1	-0.9	9.7
Total Capacity	2.1	15.4	-1.3	17.4
Average Facility Congestion, Weighted by Patients	-2.6	-14.8	1.1	-16.9
	Level Changes , Relative to Baseline			
Average Risk Adj. Survival, Weighted by Patients	0.009	0.040	-0.004	0.001
Expected Number of Life-Years Saved	3,622	16,053	-1,611	554
Medicare Expenditures ($ Millions)	1,292	12,924	499	6,524
Total Welfare ($ Millions)	700	7,857	-446	4,699
Consumer Surplus ($ Millions)	65	789	-35	422
Producer Surplus ($ Millions)	635	7,069	-412	4,277
Cost Per Life-Year Saved ($ Millions)	0.357	0.805	-	11.776

gestion which will in turn reduce the cost of quality. On the other hand, the additional entry will affect the quality elasticity of demand, possibly lowering it if patients are free to sort to new providers that are desirable for reasons other than clinical quality. The simulations show that on net additional entry induces improved quality among providers', however, subsidizing entry would be a very expensive way of promoting quality.

The entry subsidy is implemented by refunding 10% of entry costs back to the firm. This includes the constants, the cost of dialysis stations, and those factors that are specific to each entrant such as population density and chain-affiliation. The results in Table 15 show that simply increasing the number of providers and capacity is sufficient to improve clinical quality and welfare. The policy subsidizing 10 percent of entry costs (i) increases the number of entrants by 9.7 percent, (ii) the number of dialysis stations by 17.4 percent, (iii) improves clinical quality by 0.001 percentage points, and (iv) consumer surplus by almost $422 million. These are substantial gains but directly subsidizing entry is costly. On the one hand, the pass-through rate from this policy is much higher than change the reimbursement rate. The 10 percent entry subsidy produces $4.7 billion in welfare gains but costs $6.5 billion to implement. On the other hand, producers still captures over 90% of the pass through. Additionally, the increase in consumer surplus is almost entirely from

decreased congestion and travel costs. If the regulator values clinical quality more than consumer surplus, then this policy may not be appealing. The small response of clinical quality to entry subsidies illustrates how this model allows for competition on two margins: capacity and quality. Since this policy essentially decreases the cost of capacity, it is not surprising that there is a capacity response. However, this does not results in higher clinical quality as well, even though the added capacity is bringing down the cost of quality.

Policies that facility at entry without direct subsidies could be beneficial through these same channels. For example, a bill passed by the House of Representatives in the summer of 2017 allows for an easier path for facilities to become certified by CMS. Similarly, certificate of need laws may unnecessarily restrict entry and reduce consumer surplus.

8.4 Travel Subsidies

I present simulation results for a counterfactual in which the government subsidizes patient travel. When travel costs are reduced providers face additional competition from rivals at greater distances. This may improve consumer surplus through three channels. First, since providers become more substitutable it may intensify quality competition and lead to better outcomes among patients. Second, it may improve consumer surplus through more efficient sorting on other attributes such as congestion, chain-affiliation, and unobserved attributes. Third, these represent a transfer from the regulator to patients, which will directly increase consumer surplus. To implement this counterfactual I first assume regulators reimburse patients the full cost of their travel up to two miles. In a second counterfactual I assume regulators reimburse patients the full cost of their travels to any facility within their CBSA. The regulator pays for this by covering the patients' travel costs, including both the opportunity cost of the patient's time and transportation costs. To see how this is computed, see Appendix Section G.

Table 16 shows the effects of the travel subsidy. By reducing the patient's horizontal preferences, providers must focus more on differentiating themselves through dialysis quality. Providing more quality increases variable costs which diminishes producer surplus and leads to less entry. These subsidies increase consumer surplus by directly reducing the disutility from travel, by enabling patients to sort to better and less congested facilities, and by incentivizing better quality of care from providers. Travel subsidies actually result in reduced entry. Despite this, on average patients are treated at less congested facilities. This suggests that patients are able to sort more efficiently to facilities with spare dialysis capacity. The simulations also show that patients go to facilities that risk adjusted survival rates that are 0.4 percentage points higher, on average. Through these channels, the program subsidizing two miles of travel and which I estimate to cost $378 million per year, increases consumer surplus by $435 million. Because of a huge loss in producer

Table 16: Counterfactual III, Travel Subsidies

Policies	Travel Subsidies	
	Up to Two Miles	All Travel Within CBSA
	Percent Change, Relative to Baseline	
Number of Entrants	-5.6	-8.1
Total Capacity	-5.7	-7.2
Average Dialysis Congestion, Weighted by Patients	-10.0	-13.4
	Level Changes, Relative to Baseline	
Average Risk Adj. Survival, Weighted by Patients	0.004	0.031
Expected Number of Life-Years Saved	1,564	12,412
Medicare Expenditures ($ millions)	378	5,402
Total Welfare ($ millions)	-3,465	-3,113
Consumer Surplus ($ millions)	435	3,528
Producer Surplus ($ millions)	-3,900	-6,641
Cost Per Life-Year Saved ($ millions)	0.242	0.435

surplus, the overall result is a decrease in total welfare. However, if the objective of the regulator is to maximize consumer surplus and minimize expenditures without regard to producer surplus then the travel subsidy may offer a cost-effective improvement. This also proves to be the most cost-effective policy for decreasing the survival rate.

9 Conclusion

Provider market power not only allows providers to persist in the market despite offering low quality levels, but it also allows providers to capture surplus from the regulator's payments for care. The counterfactual results show that efforts to improve consumer surplus or patient outcomes are very costly. This is because increasing quality is very costly to providers and patients are not particularly responsive to quality. Providers can compete more effectively on other margins, such as capacity. Consequently, reforms that increase payments to providers and rely on market forces to translate the additional spending into improved quality will be very costly. However, regulation that effectively reduces provider market power, such as travel subsidies, can force providers to compete more intensely on quality. This transfers surplus from providers, in the form of profits, to consumers, in the form of better care. I find that this type of regulation can improve

patient welfare and outcomes without paying increasing payments to providers.

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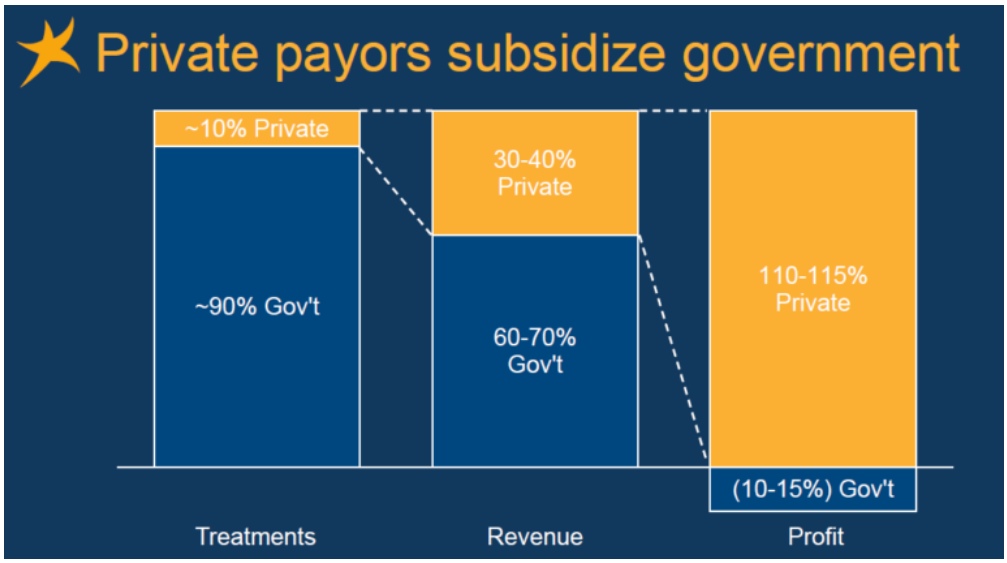
A DaVita: Private insurance subsidizes Medicare



B Data Construction

USRDS is the central clearing house for data related to ESRD prevalence and treatment in the US. It is maintained and funded by the National Institute of Diabetes and Digestive and Kidney Diseases, part of the National Institutes of Health. Drawing from Medicare claims, Medicare Administrative files, facility surveys and additional data submitted by providers, the USRDS analysis files provide the most complete data available on both the demand (patients) and supply (dialysis providers) sides of the dialysis market.

This analysis relies on comprehensive data provided by the US Renal Data System (USRDS).[30] A key strength of the USRDS data is that it contains data on nearly all ESRD patients in the US, not just the Medicare patients. Two data sources allow this. First, CMS requires a Medical Evidence Form[31] for every new dialysis patient. The primary purpose of this form is to document the date a patient began dialysis and, if that patient had private insurance, when the Medicare-Commercial coordination period began. This helps CMS determine who is on the hook for the dialysis bill—the private insurer or Medicare. However, this form also provides rich patient-level data for Medicare and privately insured patients alike, including employment status, ZIP code of residence, a measure of residual kidney function, comorbid conditions, and more health-related data. The second way USRDS collects data for patients of all payers is through the Consolidated Renal Operations in a Web-Enabled Network (CROWN) data system. Employees at dialysis facilities report data about patients, diagnostics, and treatment into this system at the point of provision. In 1995, reporting data on non-Medicare patients to the CROWN system became mandatory. This data

[30] See `www.usrds.org`.
[31] Form CMS-2728-U3.

contain the location, modality, and date of almost every dialysis treatment administered to patients in the system.

B.1 Patient data

I combine data from various USRDS Standard Analysis Files to create a cross-sectional patient data set. These include: The Patient file, Residence file, Payer History file, Treatment History file, Medical Evidence file, and Medicare Institutional Claims files. The Medical Evidence file provides valuable patient-level data, including comorbid conditions (e.g. diabetes, congestive heart disease, and others), weight, BMI, age, rage and employment status at the time of beginning dialysis. It also provides the results from a glomerular filtration rate (GFR) test. This test measures of how much blood passes through the kidneys each minute and contains information on the severity of the patient's kidney failure.

The Payer History file has longitudinal data on the type of insurance covering each patient, though not the specific plan. The Residential file provides longitudinal data on the ZIP code of residence for each patient. I geocode these to the ZIP code centroid and compute straight-line distances between patients and dialysis facilities to proxy for travel distance.

The Treatment History file allow me to observe the facilities where each patient sought treatment. The Medicare claims files provide data on the quality of treatment received at each facility, as well as how must each provider was compensated for providing treatment. I collapse these files to create a yearly panel-data set of patients. For patients who were treated are more than one dialysis facility, I assign them to their modal facility.[32] In the next section I discuss how I collapse and process the quality data.

B.1.1 Outcomes

One reason why dialysis is an ideal setting for this research is because of the richness of outcome data. I use these outcome to infer quality. The advantage of dialysis is that a number of these outcomes can be directly attributed to the provider, rather than the product of both provider practices and unobserved patient factors. I focus on five patient-level outcomes contained in the data. The first four outcomes are only available through the Medicare claims and, consequently, I can only see them for Medicare patients.

First, I will evaluate dialysis quality using the reported URR from the Medicare claims. These are available only for Medicare beneficiaries. I collapse these to a yearly frequency by computing the percent of

[32] My results are robust to specifications where I restrict the sample to patients who had one provider and where I only include patients who say their modal provider at least 75% of the year.

treatments that resulted in a URR over 65 for each patient:

$$y_{ijt}^{URR} = \frac{\text{Number of treatments with URR>65}}{\text{Total number of treatments}}$$

To assess anemia management I use monthly HGB tests,found in the Medicare claims. I collapse these to an annual frequency in the same way I did with URR. For anemia, I assume patients treated well when their HGB levels are between 10 and 12 g/dL. I evaluate infection control by using the Medicare claims to identify episodes of hospitalization where patients were hospitalized for either a septic infection or a vascular infection.[33] I then construct an indicator for whether each patient, in each year, was hospitalized for an infection. I use these same episodes of hospitalization to count all-cause hospitalizations.

The fifth outcome is survival. USRDS uses data from the CMS Death Notification form, CROWN, and the Social Security Death Master File to establish death dates for all patients. Consequently, this is the only outcome available for both Medicare and privately insured patients.

B.2 Sepsis and Vascular Infections in Medicare Claims

I construct episodes of hospitalization to be strings of hospitalizations that are not separated by one or more days out of the hospital. I identify hospitalizations that were caused by Sepsis or vascular infections based on the ICD-9 code indicating the primary diagnosis for each stay. I flag the following codes for Sepsis or Septicemia: 038.xx, 995.90, 995.91, and 995.92. I flag the following code for vascular access infections: 996.62.

B.3 Facility Data

The facility-level data come from the CMS ESRD Annual Facility Survey. Virtually all dialysis providers are certified by CMS and participate in this survey. This data include facility address, chain affiliation, the number of dialysis stations,labor inputs, for-profit status, whether the facility is hospital-based or freestanding, and the age of the facility. USRDS defines a chain to be an organization that owns or operates 20 or more dialysis facilities. While this will capture most of the large chains, this is a conservative measurement as it excludes smaller, regional chains.

B.4 Choice sets

I restrict choice sets for each patient by excluding facilities that are located prohibitively far away from their residence. For each patient I pick a maximum distance radius and drop all the facilities located beyond

[33] See appendix ### for details on how these were coded.

that. This allows me to demonstrate variation in the attributes of providers each patient may reasonably choose from. It also reduces the computational burden of estimation. Since patients travel costs per mile differ across the country, I pick radii that are CBSA-specific,[34] setting the radius to the 90th percentile of realized travel distance.[35]

Table 17 displays summary statistics for these choice sets. In particular, this table shows that most patients face differentiated facilities in their choice sets. The median patient has a choice-set radius of 11.4 miles and has seven facilities in that radius. The median within choice-set range of travel distances for patients is 6.9 miles. The bottom panel of the table shows the mean and median range of facilities in patients' choice-sets. On average, he farthest facility in a patient's choice set is six miles farther than the closest facility. For survival quality scores the best facility has a survival z-score that is 0.75 standard deviations better than the worst facility—a difference in expected survival rates of 0.059. Similarly, the difference in expected probability of having a good dialysis treatment at the best and worst facilities is 10.2 percentage points.

Table 17: Choice Sets

		Percentiles		
	Mean	5th	50th	95th
Radius (miles)	12.0	8.5	11.4	18.8
Facilities	13	1	7	25
Within Choice-Set Variation				
	Mean Range		Median Range	
Distance	5.97		6.94	
Survival Z-score	0.75		0.58	
Dialysis Z-score	0.80		0.53	
Anemia Z-score	1.45		1.10	
Hospitalization Z-score	1.30		1.08	
Infection Z-score	1.93		1.66	

Note: 10% of patients only have one facility in choice set. The range is defined to be the maximum minus the minimum.

B.5 Markets

I use Core-Based Statistical Areas (CBSAs) as a geographic market definition. This differs from other papers that use counties (Wilson, 2016a) or Hospital Service Areas (HSAs) (Grieco and McDevitt (2017) and Cutler et al. (2015)). My data allow me to examine the validity of these three potential market definitions.

[34] For patients that do not reside in a CBSA, I pool together the patients in each state that are not in a CBSA.
[35] I choose the 90th percentile because the tail above that is extremely long.

I use on the Elzinga-Hogarty criteria to test the validity of isolated markets (Elzinga and Hogarty, 1973). Although limits to this criteria are well know (Elzinga and Swisher, 2011), it provides an intuitive guide to how to delineate geographic markets and has a history of use in hospital merger cases. The criteria is that geographic markets should be picked to minimize both the flow of patients from outside a market to dialysis facilities inside the market ("little in from outside") and the flow of patients from inside the market to facilities outside the market ("little out from inside"). Table 20 shows that only 13% of patients cross CBSA borders for treatment, while over 30% cross HSA or county borders. One contributor to this is that CBSAs are larger than counties or HSAs. Market definitions that are too large run the risk of lumping together actors that, in reality, have no effect on each other. As long as this measurement error is not systematic I can interpret any market-level results as conservative estimates.

C Quality Value Add Regressions

Table 18: Facility Value Add Regressions

	Dependent Variables				
	Pr(Survival)	Dialysis Adequacy	Anemia Treatment	Log(Hospitalizations)	Pr(Hosp. for Infection)
Male	-0.004	-0.075	-0.017	-0.044	-0.004
	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0002)
Hispanic	0.051	0.038	0.005	-0.056	-0.008
	(0.0006)	(0.0004)	(0.0005)	(0.0009)	(0.0003)
Black	0.042	-0.005	0.009	-0.039	-0.002
	(0.0004)	(0.0003)	(0.0004)	(0.0007)	(0.0003)
Asian	0.068	0.049	0.015	-0.149	-0.016
	(0.0009)	(0.0008)	(0.0009)	(0.0016)	(0.0006)
Other Race	0.031	0.019	0.001	-0.051	-0.004
	(0.0008)	(0.0006)	(0.0007)	(0.0013)	(0.0005)
Hypertension	0.026	0.007	0.004	-0.024	-0.009
	(0.0004)	(0.0003)	(0.004)	(0.0007)	(0.0002)
Diabetes	-0.026	-0.015	0.009	0.061	0.011
	(0.0003)	(0.0002)	(0.0003)	(0.0006)	(0.0002)
Congestive Heart Disease	-0.045	-0.011	0.004	0.069	0.007
	(0.0004)	(0.0003)	(0.0003)	(0.0006)	(0.0002)
Vascular	-0.026	0.002	-0.001	0.054	0.013
	(0.0006)	(0.0004)	(0.0005)	(0.0010)	(0.0003)
Employed	0.026	0.005	-0.005	-0.077	-0.012
	(0.0005)	(0.0004)	(0.004)	(0.0008)	(0.0003)
Private Insurance	0.013				
	(0.0006)				
Medicare Advantage	0.006				
	(0.0006)				
Medicaid	-0.013				
	(0.0004)				
Unknown Payer	-0.040				
	(0.0006)				
Age, Years on dialysis Controls	X	X	X	X	X
BMI Bin FEs	X	X	X	X	X
GFR Bin FEs	X	X	X	X	X
Facility * Year FEs	X	X	X	X	X
N	5441664	3802739	4147744	4211122	4211122
R-squared	0.18	0.19	0.08	0.30	0.08

D Payment Summary Statistics

Table 19: Mean Payments Per Dialysis Session

	Service Provided			
	Dialysis	EPO	Other	All Services
Medicare Portion	130.99	39.20	20.22	190.41
Beneficiary Portion	32.75	8.55	5.06	47.60
Total Payment	163.74	47.75	25.28	238.01

Note: Pools data from 1998 to 2012. In 2012 EPO and dialysis payments were bundled into a single prospective payment, the payment level of which was adjusted to be equal to a historical sum of dialysis payments and EPO payments, with a 2% reduction. These bundled payments are included in the dialysis category, inflating that mean in years 2011 and 2012, while corresponding zeros for EPO payments reduce the reported average EPO payment.

E Evaluation of Alternative Market Definitions

Table 20: Elzinga-Hogarty Criteria

	Percent of patients treated outside of their market of residence
CBSAs	0.13
HSAs	0.33
Counties	0.32

F Reduced From—Extended results

F.1 First Stage of Tradeoff Regressions

Table 21: Tradeoff Regressions, First-Stage

	Dependent Variable: $\ln(\mathcal{C}_{ij^*}/\mathcal{C}_{ij^{closest}}+1)$				
Instrument ($\ln(\hat{\mathcal{C}}_{ij^*}/\hat{\mathcal{C}}_{ij^{closest}}+1)$)	0.15***	0.16***	0.15***	0.14***	0.14***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Survival Difference	-0.10***				
	(0.004)				
Dialysis Quality Difference		0.02***			
		(0.003)			
Anemia Quality Difference			-0.03***		
			(0.004)		
Hospitalization Difference				0.01***	
				(0.002)	
Infection Difference					0.02***
					(0.001)
Year FE	X	X	X	X	X
F-statistic	87.68	68.63	78.38	56.53	69.76

F.2 Tradeoff Regressions, Alternative Measures of Clinical Quality

Table 22: Location and Quality Tradeoffs, Other Quality Measures

	Dep. Var.: $\text{Log}(Dist^{choice}/Dist^{Closest}+1)$					
	OLS	IV				
Difference in Anemia Z-score	0.04***	0.12***				
	(0.007)	(0.010)				
Difference in Hospitalization Z-score			0.04***	0.112***		
			(0.009)	(0.011)		
Difference in Infection Z-score					-0.01	0.01
					(0.005)	(0.007)
Congestion	0.36***	-1.50***	0.36***	-1.59***	0.37***	-1.56***
	(0.014)	(0.103)	(0.014)	(0.112)	(0.014)	(0.111)
Year FE	X	X	X	X	X	X

Table 23: Location and Quality Tradeoffs

Dep. Var.: $\text{Log}(Dist^{choice}/Dist^{Closest}+1)$		
	OLS	IV
Difference in Quality Z-scores		
Survival z-score	0.03	0.12***
	(0.015)	(0.018)
Dialysis z-score	0.05***	0.08***
	(0.012)	(0.014)
Anemia Z-score	0.01	0.05***
	(0.007)	(0.009)
Hospitalization Z-score	0.02*	0.05***
	(0.009)	(0.012)
Infection Z-score	-0.02*	-0.01
	(0.008)	(0.009)
Congestion	0.35***	-1.22***
	(0.020)	(0.089)
Year FE	X	X

F.3 Allocation Regression

Table 24: Allocation Regressions, Other Quality Measures

Dependent Variable: Log(Patients)	(1)	(2)	(3)	(4)	(5)	(6)
Anemia Z-Score	0.04	0.02				
	(0.037)	(0.041)				
Log(Market PPS)*Anemia	0.02	0.03				
	(0.020)	(0.022)				
Hospitalization Z-Score			-0.08*	0.00		
			(0.033)	(0.039)		
Log(Market PPS)*Hospitalization			0.06***	0.02		
			(0.018)	(0.022)		
Infection Z-Score					-0.07*	0.00
					(0.034)	(0.041)
Log(Market PPS)*Infection					0.05*	0.01
					(0.020)	(0.024)
Log(Market PPS)	0.47***	0.061	0.46***	0.61***	0.46***	0.61***
	(0.021)	(0.031)	(0.021)	(0.031)	(0.021)	(0.031)
Log(Number of Stations)	1.13***	1.14***	1.14***	1.16***	1.14***	1.16***
	(0.019)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)
Log(Predicted Caseload)	0.22***	0.26***	0.21***	0.25***	0.21***	0.25***
	(0.015)	(0.017)	(0.015)	(0.018)	(0.015)	(0.018)
Private Insurance Share, Market Level	-1.63***	-1.76***	-1.63***	-1.72***	-1.62***	-1.70***
	(0.124)	(0.126)	(0.125)	(0.127)	(0.124)	(0.126)
Log(Facility Age)	0.21***	0.22***	0.21***	0.22***	0.21***	0.22***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Freestanding	-0.03	0.05	0.01	0.09**	0.02	0.09*
	(0.025)	(0.030)	(0.025)	(0.029)	(0.025)	(0.029)
For-Profit	0.09***	0.15***	0.08***	0.14***	0.09***	0.14***
	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)
Year FE	X	X	X	X	X	X
CBSA FE		X		X		X

Notes: Standard errors clustered at facility level. Predicted caseload refers to the caseload predicted by a MNL model using only distance from patients to the facilities in their choice sets. Here it is used to control for the fact that some facilities are physically located closer to more patients than others.

Table 25: Provider Response to Rival Congestion: First stage

Dependent variable:	Log(PPS), own facility	Log(PPS), rival facilities	Log(PPS), own facility	Log(PPS), rival facilities
Log(Predicted patients per station), own facility	0.28***	-0.10***	0.34***	-0.04***
	(0.011)	(0.005)	(0.003)	(0.002)
Log(Predicted patients per station), surrounding facilities	-0.03***	0.61***	0.05***	0.70***
	(0.010)	(0.012)	(0.005)	(0.002)
Own PI Share	0.77***	0.14**	1.02***	0.04*
	(0.100)	(0.036)	(0.037)	(0.019)
Rival PI Share	-0.14	0.38*	-0.16*	0.21***
	(0.116)	(0.191)	(0.079)	(0.041)
PI Share in 15-mile Radius	-1.55***	-1.46***	-1.14***	-1.12***
	(0.142)	(0.155)	(0.092)	(0.048)
Log(Facility Age)	0.11***	-0.01***	0.11***	-0.02***
	(0.003)	(0.002)	(0.002)	(0.001)
For-Profit	0.02	0.02*	0.02***	-0.02***
	(0.013)	(0.008)	(0.005)	(0.003)
Freestanding	0.07***	-0.04**	0.13***	-0.02***
	(0.020)	(0.011)	(0.006)	(0.003)
Year FE	X	X	X	X
Market FE			X	X
F-statistic	83.05	181.51	720.78	4018.65

Predicted facility shares based on a MNL logit model estimated using only geography–distance from each patient's residence to the facilities in their choice set, interacted with CBSA.

F.4 Provider Response to Rival Congestion, Tables

F.5 Private Insurance and Market Share

I investigate the determinants of market structure in a descriptive way. To do this I estimate a market-level regression to infer the influence of states on the observed capacity levels. I am primarily interested in how patients with different payer types (Medicare vs. private insurance) influence the levels of dialysis capacity. Geographic variation in resources and access is common in health care. Here, however, we may have an observed and plausibly exogenous shifter in those resources—the share of patients with private insurance.

Table 26: Provider Response to Rival Congestion: Other Outcomes

Dependent variables:	Anemia Z-Score		Hospitalization Z-Score		Infection Control Z-Score	
	OLS	IV	OLS	IV	OLS	IV
Log(Patients Per Station), own facility	-0.09***	-0.29***	-0.02	-0.05	-0.08***	-0.03
	(0.027)	(0.055)	(0.023)	(0.056)	(0.024)	(0.054)
Log(Patients Per Station), surrounding facilities	-0.12***	-0.023	-0.01	-0.05	0.05	-0.03
	(0.022)	(0.030)	(0.029)	(0.036)	(0.024)	(0.030)
Own PI Share	-1.25***	-0.98***	0.03	0.10	-1.55***	-1.65***
	(0.204)	(0.209)	(0.210)	(0.217)	(0.194)	(0.207)
Rival PI Share	-0.71**	-0.75**	1.03***	1.05***	0.44	0.46
	(0.244)	(0.250)	(0.310)	(0.314)	(0.283)	(0.290)
PI Share in 15-mile Radius	0.77**	0.44	0.94*	0.83*	0.39	0.46
	(0.311)	(0.330)	(0.368)	(0.384)	(0.341)	(0.357)
Log(Facility Age)	0.03***	0.05***	-0.05***	-0.05***	-0.03***	-0.04***
	(0.008)	(0.004)	(0.009)	(0.011)	(0.008)	(0.010)
For-Profit	-0.07**	-0.07**	0.15***	0.15***	0.09**	0.08**
	(0.024)	(0.024)	(0.028)	(0.028)	(0.028)	(0.029)
Freestanding	0.68***	0.068***	0.22***	0.22***	0.08*	0.07
	(0.052)	(0.054)	(0.048)	(0.048)	(0.039)	(0.039)
Year FE	X	X	X	X	X	X

Includes only specification without market fixed effects. Predicted facility shares based on a MNL logit model estimated using only geography–distance from each patient's residence to the facilities in their choice set, interacted with CBSA.

I estimate the following regression:

$$k_{mt} = \beta_0 + \beta_1 \text{Medicare Patients}_{mt} + \beta_2 \text{PI Patients}_{mt} + \Gamma X_{mt} + \mu_t + \lambda_m + \varepsilon_{mt} \tag{17}$$

The dependent variable is a measure of dialysis capacity in market m and year t. This measure can be the number of dialysis stations or the number of dialysis facilities. I define markets as CBSAs. I control for market characteristics such as population density and include year and market fixed effects.

Table 27: Determinants of Market Structure

Dependent variable:	Number of Dialysis Facilities		Number of Dialysis Stations	
	(1)	(2)	(3)	(4)
Number of Medicare Patients	0.005***	0.008***	0.126***	0.191***
	(0.0001)	(0.0001)	(0.0011)	(0.0012)
Number of Private Insurance Patients	0.055***	0.028***	0.658***	0.393***
	(0.0010)	(0.0012)	(0.017)	(0.017)
Year FEs	X	X	X	X
Market FEs		X		X
R-squared	0.95	0.95	0.95	0.95
Adj. R-squared	0.95	0.95	0.95	0.95

*

G Travel Costs

G.1 Monetizing Consumer Surplus

I convert consumer surplus from utility to dollars by calibrating the cost of travel, in terms of dollars per mile, and using it to transform utility to dollars. In this calibration I assume the cost of travel has two parts: the opportunity cost and the accounting cost. The opportunity cost is equal to the time of travel times the opportunity cost of time. I assume the time of travel to be the straight-line distance divided by 35. The straight-line distance understates the actual distance, so the monetized estimate of consumer surplus should be thought of as a lower bound. I assume the opportunity cost of time to be the minimum wage. This can also be thought of as a lower bound. I use estimates of the accounting cost of travel from Godavarthy et al. (2014). I assume half of patients are chauffeured by a family member or friend, while the other half take a taxi. I also use their cost estimates for the two types of transport: $1.05 per mile for chauffeured trips and $2.25 for taxis. This results in an average travel cost of $1.86 per mile. I account for both directions. Consumer surplus, denominated by dollars, is utility divided by the coefficient on travel costs from the demand estimates (which has units of utility per mile) multiplied by the travel cost (dollars per mile).

G.2 Estimating the cost of travel subsidies

The travel subsidy program consists of cash transfers to patients that are equivalent to the consumer surplus from travel. This includes the opportunity cost as well as the transportation cost. The regulator reimburses patients for their opportunity cost using the same formula as above, multiplying the expected

travel time by the minimum wage. To compute the transportation cost I use average taxi costs for urban and rural areas from Godavarthy et al. (2014), including the base rate ($2.25 for urban routs and $8.00 for rural routes) and the per-mile rate ($2.25 per mile). I account for both directions of this trip.

I use these same values to estimate the cost of transportation subsidies in the counterfactuals.