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Market Structure as a Determinant of Patient Care Quality: The Importance of Controlling for Specialization

Nathan E. Wilson *†

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Abstract

When deciding what treatment to receive, patients can be expected to evaluate how their predicted outcomes vary across their choices. Traditionally, econometric approaches to accounting for this selection process have focused on unobservable variation in condition severity, but assume homogeneous responsiveness to treatment. To relax this strong assumption, I develop a control function approach to estimating patient outcome models. The method is applied to data on dialysis patients in the metro Atlanta area between 2004 and 2008. Specification tests suggest that controlling for heterogeneous response to treatment at different facilities is important in identifying the mean impact of facilities on patient outcomes. Decomposing the estimates of treatment center quality on market and facility characteristics, I find evidence that concentration is negatively associated with treatment quality.

JEL Codes: C3, I11, L1, L33
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*The views expressed in this article are those of the author. They do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. Contact: 600 Pennsylvania Avenue NW, M-8059, Washington DC, 20580. Phone: 202-326-3485. E-mail: nwilson@ftc.gov.

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1 Introduction

In health-care contexts, interest in the relationships between competition, ownership structure, and quality is acute, and opinions are particularly divided. For example, economic models strongly suggest that competition should increase quality, especially in regulated price settings (Gaynor, 2006).[1] While many economic studies have found evidence consistent with this claim (Gaynor and Town, 2011), it is important to note that not all have done so (Gowrisankaran and Town, 2003, Grieco and McDevitt, 2012, Mukamel et al., 2001). This ambiguity has helped to underpin many clinicians' and politicians' concerns that competition and the profit motive produce a fragmented industry where participants have little incentive to control wasteful investment or provide high quality care (Enthoven and Tollen, 2005, Mays, 2011).

At first, the marked lack of consensus about such important issues may seem surprising. After all, various databases track patient-utilization and outcomes, making it seemingly straightforward to construct and compare outcome-based measures of quality.[2] However, given the reasonable expectation that patients select the treatments that are most likely to benefit them, it is difficult for analysts to be sure that simple comparisons of facility averages capture the true, "causal" impact of different facility or market characteristics. For example, if higher quality treatments are associated with certain market characteristics, and unobservably sicker patients systematically prefer higher quality, then simple analyses of the impact of market structure on average quality will be biased.

Clearly, this *intercept endogeneity* (Luan and Sudhir, 2010) should be a source of significant concern in health-care settings. However, one might also worry about the possibility of expected differences in treatment across individuals, especially since the medical literature has documented considerable heterogeneity in responsiveness to treatment for many conditions (Kravitz et al., 2004), and that this heterogeneity can sometimes be attributed to demographic variation (Gabler et al.,

[1] Katz (2013) notes that under certain circumstances this relationship may fall apart, but that increases in concentration as a result of acquisitions or mergers are invariably associated with lower incentives to provide high quality care.

[2] See, e.g., Romano and Mutter (2004) on the merits of various quality metrics.

2012). In the context of medical facilities, the existence of heterogeneous treatment effects might be most easily understood if different providers engage in unobservable specialization in working with different types of patient or variants of different conditions. If observable to patients but not the econometrician, then such *slope endogeneity* would then mean that empirical methods that only account for unobserved variation in the level of sickness also produce biased estimates of the true average effect of treatment.

To address the possible importance of heterogeneous responses to treatment (i.e., random coefficients), I develop a control function (CF) approach to estimating the average quality of many different treatments, building off of previous work in the labor and marketing literatures (see, in particular, Heckman (1978), Card (2001), Luan and Sudhir (2010), Petrin and Train (2010)). The key benefit to the overall approach is that it addresses one of the biggest concerns with standard market structure models, which is that outcomes and structure are simultaneously determined. The CF model addresses this problem by controlling directly for the impact of unobserved, as well as observed, patient characteristics. Thus, the likelihood of simultaneity bias is markedly reduced since the quality estimate takes into account the types of patient being treated. Once a treatment outcome equation has been consistently estimated using my CF approach, the average estimated impact of different treatments can be collected and then decomposed on facility- and market-level factors as in the structural productivity literature (Syverson, 2011).[3]

Using comprehensive data on hemodialysis patients in the Atlanta metropolitan area between 2004 and 2008, I apply my empirical approach to identifying facility- and market-level impacts on treatment quality . For over thirty years, commentators have complained that the average quality of hemodialysis treatment in America lags that of other developed nations (Relman and Rennie, 1980, Fields, 2010a,b). This perceived quality gap has given rise to a large scholarly literature aimed at uncovering the determinants of treatment quality. Despite all the attention, however, little is well-accepted about whether or not patients' outcomes vary with factors like the ownership status

[3]A somewhat similar tactic was previously employed in analyzing hospital quality in Gowrisankaran and Town (1999).

of the facility or the degree of local competition. Addressing at most the possibility of selection based on intercept endogeneity, different papers have produced different results.[4] Moreover, neither of the most recent and econometrically sophisticated papers (Grieco and McDevitt, 2012, Cutler et al., 2012) found the expected positive relationship between quality and competition that theory strongly predicts.

My analysis of the Atlanta data strongly suggests that the lack of clarity in the previous literature may stem in part from the importance of selection due to heterogeneous treatment effects. Standard specification choice tests suggest that CF models best fit the outcome data, and tests of the implicit behavioral assumption underpinning the CF-model also support its use. Relying on the estimates of treatment quality robust to the presence of heterogeneous treatment effects leads to very different inferences about the relationships between ownership, competition, and treatment quality than other approaches. In particular, I find a robust negative correlation between concentration and quality when using the CF estimates. For example, my baseline estimates suggest that a 10 percent increase in the number of nearby affiliated facilities would lead to a greater than 15 percent increase in the average number of days a patient spent in the hospital. In contrast, I find that the results about the relationship between competition and quality are much less strong – and even sometimes inverted – when the estimates of treatment quality come from models that ignore selection on both intercept and slope unobservables. Though contrary to some of the prior literature, these results are consistent with overall economic theory.

Second, I find evidence that average treatment quality is not consistently higher at non-profit facilities. (If anything, I find weak evidence in the opposite direction.) Once more, this result runs contrary to the findings of Grieco and McDevitt (2012) and other papers in the health services literature (see, e.g., Devereaux et al. (2002)). However, it is in line with the possible explanation that for-profit facilities have an incentive to seek out sicker patients. This reflects the structure of

[4]See, e.g., Garg et al. (1999), Ford and Kaserman (2000), Devereaux et al. (2002), Brooks et al. (2006), Zhang et al. (2011), Grieco and McDevitt (2012) on the impact of ownership and Lee et al. (2010), Cutler et al. (2012), Grieco and McDevitt (2012) on the role of competition.

Medicare's compensation scheme during the sample period, which rewarded facilities based on the volume of drugs administered (Thamer et al., 2007). A focus on sicker patients by for-profit dialysis providers would broadly support the findings of Wilson (2013), who found evidence suggesting higher marginal profits at for-profit facilities.

Overall, the paper contributes to the growing literature on alternatives to the standard instrumental variables (IV) framework for addressing endogeneity concerns (Dustmann and Meghir, 2005, Liu et al., 2010, Luan and Sudhir, 2010). It extends the existing CF-related approaches in a comparatively straightforward way to accomodate the possibility of multiple endogenous treatments, an important issue in the health-care and industrial organization literatures. In addition, the paper adds to the rapidly expanding literature on the importance of market structure in health care settings (Gaynor and Town, 2011), focusing on a comparatively understudied industry relative to its impact on patient lives and the Federal budget and largely validating the concern of anttrust regulators about the consequences of increasing concentration.

2 The Empirical Model

Consistent with the prior literature (see, e.g., Gowrisankaran and Town (1999), Kessler and McClellan (2000), Geweke et al. (2003)), I assume the effects of facility choice on health outcomes can be modeled in discrete time, and that each period's decisions are independent of those that come before. Within a period, a multi-stage game maps from facilities' and patients' choices to patient outcomes. The precise steps of my approach are detailed below.

2.1 Facility Selection & Treatment Outcome

For expositional purposes, I begin with a simplified setting with just two possible places to receive treatment: A and B. The goal of estimation is to identify the quality of A relative to B. In describing how this inference might be drawn, I broadly follow the expositional approach taken in previous papers concerned with stochastic treatment effects (Card, 2001, Luan and Sudhir, 2010).

Within a given period, the game proceeds as follows. In the first stage, facilities determine what type of treatment they wish to provide, choosing a single quality type, which may heterogeneously impact patients. In practical terms, this may be thought of as developing expertise in certain types of patients. Once their choice has been made, facilities are not able to customize their quality to each patient's characteristics. In the second stage, an individual requiring dialyzation decides which facility they will visit for treatment after having observed facilities' quality decisions. Once the choice of facility is made, the outcome of treatment y_i is realized for patient i.

Defining c_i to be an indicator variable taking the value of one if patient i receives treatment at facility A, the relative benefit of receiving treatment at A is obtained by estimating the following treatment equation:

$$y_i = f(c_i, x_i|\theta_i) + \epsilon_i, \tag{1}$$

where x_i are observable confounding factors, θ_i is a vector of parameters possibly unique to patient i, $f(\cdot)$ is a possibly nonlinear function of the inputs, and ϵ is information unobservable to the econometrician.

If one makes the standard assumption that the inputs to $f(\cdot)$ enter linearly, Equation (1) can be rewritten as:

$$y_i = f(\theta_{i1} + \theta_{i2}c_i + x_i\theta_3) + \epsilon_i,$$

where the lack of a patient-specific subscript on θ_3 indicates that it is constant across the population. Following Card (2001), the elements of this equation can be divided to separate the individual-level heterogeneity from the mean effects of the different regressors:

$$y_i = f(\theta_{01} + \bar{\theta_2}c_i + x_i\theta_3 + \tilde{\theta_{i1}} + (\theta_{i2} - \bar{\theta_2})c_i) + \epsilon_i, \tag{2}$$

where $\tilde{\theta_{i1}} = \theta_{i1} - \theta_{01}$ and has mean 0.

Now, assume (as in Berry et al. (1995)) that the heterogeneity in the coefficients can be parameterized as linear functions of the observable factors x_i and some unobservable, stochastic elements.[5] This means that the random coefficients in Equation (2) can be rewritten as:

$$\tilde{\theta_{i1}} = x_i\beta^1 + \phi_i^1, \text{ and} \tag{3}$$

$$(\theta_{i2} - \bar{\theta_2}) = x_i\beta^2 + \phi_i^2. \tag{4}$$

In this case, β^1 indicates how the observable factors relate to variation in expected outcomes at the patient-level, β^2 reflects how the observables alter the marginal effect of receiving treatment at facility A, and the ϕ capture the influence of unobservable information on patients' heterogeneity, both in terms of underlying condition severity and responsiveness to treatment.

So long as the choice of treating facility occurs randomly, the assumption that the θ_i are linear functions implies that Equation (2) can be consistently estimated via ordinary least squares (OLS) if $f(\cdot)$ is a linear function. If f is nonlinear, it may still be estimated consistently using standard simulation approaches to dealing with random coefficients in nonlinear models (see, e.g., Train (2003)). However, regardless of f's functional form, problems arise if the choice of treatment facility is non-random. The most natural way of understanding this in the dialysis context would be if the patient – or their referring nephrologist or physician – possesses insight into the unobserved information (i.e., θ_{i1}, θ_{i2}, or ϵ_i) in the treatment equation. Knowledge about these parameters would then be expected to affect the choice of facility. If the goal is to subsequently evaluate what factors may be influencing $\bar{\theta_2}$, such bias is of major concern.

There is a large literature in health care suggesting that this sort of selection bias occurs and has economically meaningful effects on estimates if left unaddressed (Gowrisankaran and Town, 1999, Kessler and McClellan, 2000, Geweke et al., 2003, Varkevisser et al., 2012). To address the

[5] In practice, it is likely that only a subset of the observables x impacts the random coefficients; however, for notational ease, I simply use x.

problem, health economists have typically turned to IV methods, which allow the endogenous choice of treating facility is allowed to be correlated with the random intercept term θ_{i1} in Equation (2). However, the possibility of heterogeneous treatment effects (i.e., $\theta_{i2} \neq \bar{\theta_2}$) is precluded. Thus, the standard approach addresses the concern that sicker patients will choose better facilities (i.e., *intercept endogeneity*), but leaves unaddressed any problems stemming from variation in responsiveness to facilities' treatments (i.e., *slope endogeneity*). Worrisomely, this means that not only will estimation methods that ignore any possibility of selection bias be inconsistent, but so will the standard IV estimator (Card, 2001).[6]

I address these problems by using an approach that permits both random parameters, θ_{i1} and θ_{i2}, to influence the choice of treatment facility c_i. I begin – as in standard IV – by assuming that the choice of facility, c_i, is a function not just of the observables included in Equation (1), but also a set of exogenous variables z_i that do not influence y_i except through their influence on c_i (i.e., instruments). Health scholars have long assumed that patients' travel distances satisfy these criteria, as the selection of a treating facility will be influenced by the patient's travel cost of reaching it, but travel distance should not independently influence their outcomes.[7] Thus, assuming a linear probability model, the likelihood that a patient elects treatment at A can be written as:

$$c_i = z_i\gamma + \eta_i, \tag{5}$$

where for the sake of simplicity of exposition the observable variables x_i are collapsed into z_i. Provided that the choice model is correctly specified, the error term should be uncorrelated with the instruments, i.e., $E[\eta|z] = 0$.

One additional assumption is required before the treatment equation is estimated. This critical requirement is that the unobservables from Equations (3) and (4) are mean independent of the

[6]Moreover, even if there is no slope endogeneity (i.e., $\beta_{i2} = \bar{\beta_2} \forall i$), standard IV estimation will lead to inconsistent estimates if f is nonlinear as shown in Terza et al. (2008a,b).

[7]See, e.g., Gowrisankaran and Town (1999), Kessler and McClellan (2000), Gaynor et al. (2005), Brooks et al. (2006), Ho (2006), Lee et al. (2010).

instruments z_i after conditioning on η_i. Formally, this means that $E[\phi|z,\eta] = E[\phi|\eta]$. In practice, the assumption implies that the stochastic heterogeneity in responsiveness to treatment, ϕ^2, can be modeled as a function of the random elements impacting the choice of facility, η. In other words, $E[\phi|\eta] = g(\eta)$. In the context of dialysis facility choices, this assumption means if observables suggest that a patient should choose treatment at facility A, but she does not, then this likely reflects something correlated with her expected outcome from treatment there. I follow the convention of assuming that this conditional expectation can be modeled using its linear approximation (Petrin and Train, 2010).

Altogether, these assumptions imply that Equations 3 and 4 can be rewritten as:

$$\tilde{\theta_{i1}} = x_i\beta^1 + \phi_i^1 = x_i\beta^1 + \psi\eta_i, \text{ and} \tag{6}$$

$$(\theta_{i2} - \bar{\theta_2}) = x_i\beta^2 + \phi_i^2 = x_i\beta^2 + \tau\eta_i \tag{7}$$

Collecting Equations (6) and (7) and substituting them back into Equation (2) implies that the treatment equation itself becomes:

$$y_i = f(\theta_{01} + \bar{\theta_2}c_i + \overbrace{\psi\eta_i + \tau\eta_i c_i}^{\text{control function}} + x_i\tilde{\theta_3}) + \epsilon_i, \tag{8}$$

where $\tilde{\theta_3}$ captures the impact of the observables directly on outcome as well as their impact on the deterministic portion of the heterogeneous coefficients (i.e., $\tilde{\theta_3} = \theta_3 + \beta_1 + \beta_2$).

By including the control function of the residuals from the facility choice equation in Equation (8), one can consistently estimate the mean impact of receiving treatment at facility A rather than B, $\bar{\theta_2}$. It accounts for both sources of bias discussed above. Moreover, IV estimation of Equation (8) would not be consistent because of the influence of the slope endogeneity component. This is because even if $E[\phi^1|z] = 0$, $E[\phi^2 c|z] \neq 0$ unless strong assumptions hold about both the orthogonality of the product of the endogenous variables and their residuals and the homoskedasticity of the residuals. This is generally untrue (Heckman and Vytlacil, 1998). In contrast, the CF approach of including

the residuals from the first stage and the interaction of that residual with the endogenous variable will produce consistent estimates via standard estimation techniques for dealing with f.

Within the control function, τ tells us something about the relationship between the individual-specific responsiveness to treatment at A and the decision to actually receive treatment there. A positive coefficient would indicate that persons whose observables suggest that they are unlikely to receive treatment at A, yet choose to do so, are disproportionately likely to benefit from receiving treatment there (assuming that y is a positive, desirable outcome). Thus, one can by examining $\hat{\tau}$ check the validity of the behavioral assumption underpinning the model.

2.2 Empirical Specification with Multiple Endogenous Treatment Options

This paper's primary technical innovation is to suggest a means of moving from the one endogenous treatment setting described above to one where there is more than one endogenous treatment variable. This requires the specification of the choice set of facilities available to each patient, as well as the process by which a facility is chosen. In addition, I must express the appropriate control function given that there will be more than one endogenous variable. As discussed below, theory and the existing literature suggest straightforward ways of addressing both issues.

Consistent with the prior literature on patient choice modeling (Kessler and McClellan, 2000, Tay, 2003, Ho, 2006), I assume that each patient considers each facility within some radius of their home. All of the different facilities j of a possible J within the specified radius provide patient i a distinct level of utility:

$$V_{ij} = m(d_{ij}, k_{ij}) + \mu_j + e_{ij}, \tag{9}$$

where $m(d_{ij}, k_{ij})$ is a function of the distance d between the patient's zipcode and the facility's zipcode and a set of patient or facility characteristics k, μ_j is a facility fixed effect, and e_{ij} is information unobserved by the econometrician that affects the desirability of seeking treatment at j.

If the e_{ij} are independent across alternatives, then the utility that a patient receives from choosing a given facility is independent of its other choices, and implies that Equation (9) can be estimated via conditional logit. This assumption is common in the literature (Capps et al., 2003, Ho, 2006), and seems reasonable in this particular case. Following estimation, I use the recovered coefficients to predict the likelihood that patient i chooses facility j. These predictions are then subtracted from the binary indicator variable capturing whether or not patient i actually does choose to visit facility j to produce an η_{ij} for each possible j of J.[8] I impose that $\eta_{ij} = 0$ for all facilities outside the specified choice radius.[9]

The multiplicity of η that the procedure above produces requires alterations to Equation (8). In particular, the nature of the interactions between the residuals and the endogenous variable must be specified. As shown in Luan and Sudhir (2010), without assumptions about the relationship between the error terms in the first stage models, including J endogenous variables implies that the control function should include the J residuals directly plus J^2 interaction terms. These interactions account for the possibility that the unobservable information affecting the selection of an endogenous variable also affects the responsiveness to another.

In many cases, including that of Luan and Sudhir (2010), controlling for the possibility of such interrelatedness seems both reasonable and appropriate. However, in my setting, it is unduly conservative, running contrary to the assumption made in estimating the facility choice model that the error terms impacting the utilities of the different options are independent. Therefore, it is reasonable to believe that the only residual impacting the slope a given endogenous variable is the one from its own first-stage equation. These assumptions imply that the control function, which took the form $\psi\eta_i + \tau\eta_i c_i$ when there was only one endogenous element, generalizes to $\sum_{j=k}^{K} \psi_j \eta_{ij} + \tau_j \eta_{ij} c_{ij}$

[8] This ensures that the error terms are broadly proportional in magnitude to the endogenous regressors, which may be important in small samples or non-linear settings.

[9] This conditional logit approach departs from the approach taken in Gowrisankaran and Town (1999), who used a dichotomous discrete choice model and a non-linear function of distance to estimate whether or not a given patient chose each possible hospital.

when there are K endogenous elements. Thus, the baseline estimating equation becomes:

$$y_{ij} = f(\bar{\theta_j} c_{ij} + \overbrace{\sum_{i=k}^{K} (\psi_j \eta_{ij} + \tau_j \eta_{ij} c_{ij})}^{\text{control function}} + x_{ij}\tilde{\theta_3}) + \epsilon_{ij}, \tag{10}$$

where time subscripts are suppressed for the sake of concision.

2.3 Inferring Determinants of Quality

Once the facility-specific average quality coefficients have been consistently estimated ($\hat{\bar{\theta}}$) using Equation (10), insight into how different market-level and facility-level factors influence treatment quality can be gained by decomposing them. This idea owes much to the structural productivity literature (Syverson, 2011), and a related approach was previously employed by Gowrisankaran and Town (1999) in analyzing the impact of hospital ownership on patient mortality after controlling for the possibility of selection based on unobserved condition severity.

In my analyses of patient outcomes, I pool all observations and estimate an individual, time invariant quality effect for each facility. These fixed quality effects are then collected and regressed on the average values of market structure, the facilities' modal ownership status, and other facility-specific characteristics. Thus, to understand the relationship between quality at facility j and market or facility characteristics, I estimate the following regression:

$$\hat{\bar{\theta}}_{jm} = \bar{M}_{mj}\beta + e_{jm}, \tag{11}$$

where M is a vector of market- and facility-level characteristics and m indexes markets. The impacts of the different factors are identified off of cross-sectional variation across facilities.

It is useful to think carefully about why Equation (11) is an improvement on the standard endogeneity concerns about cross sectional market structure analyses (Berry and Reiss, 2007). In many circumstances, one worries about the regression of an outcome variable like price, profits, or

quality on market structure measures. This is because one might reasonably be concerned that the outcome variable is simultaneously influencing the regressors. For example, if a given local population was of unobservably good health, making them cheaper to treat, then one might expect greater than otherwise expected entry. Naive regressions of quality on market structure would then falsely suggest a stronger than "true" relationship between competition and quality. In addition, if facilities specialize as hypothesized in the empirical model, and increased competition leads to greater specialization, then the result will be raw quality estimates that are increasingly contaminated by strategic selection effects as competition increases.

The CF approach developed and employed in this paper explicitly addresses these possible concerns. Whereas a "raw" measure of quality would reflect both unobserved condition severity and the possibility that some stations specialize, the quality estimates from the CF are purged of these influences. Thus, a simple regression of the estimated quality metric on the market structure proxies should be expected to consistently capture the "true" impact of competition, making it unnecessary to rely on instruments or plausibly exogenous shocks to market structure.

3 Institutional Background & Data

3.1 Background

A diagnosis of end stage renal disease (ESRD) means that an individual has permanently lost kidney function.[10] ESRD generally arises as a consequence of chronic kidney disease, coronary disease, hypertension, diabetes, and other progressive, chronic conditions. Invariably fatal without treatment, ESRD can be treated either through chronic dialyzation or transplant. Given the marked lack of kidneys available for transplant, the vast majority of ESRD patients regularly receive some form of dialysis. By far the most common modality ($\approx$ 90% of patients) is hemodialysis, which pumps patients' blood through a machine that replicates the cleaning process typically performed by functioning kidneys. Though sometimes done in hospitals, patients generally undergo hemodialysis

[10]For in depth treatments of ESRD, see Farley (1993), Wilson (2013), or the citations therein.

treatment in specialized facilities supervised by clinicians. The most common alternative modality is peritoneal dialysis, wherein patients receive injections of a cleansing dialysate that must be replaced every few hours. This may occur either in patients' homes or in facilities.[11]

The incidence – meaning the commonality of new diagnoses – of ESRD has risen dramatically over the last quarter century: overall, it increased from less than 0.1 percent to 0.35 percent of the entire U.S. population between 1980 and 2008 (USRDS, 2011). This dramatic increase in the commonality of ESRD has had grave implications for Federal expenditures, for all Americans suffering from ESRD are eligible to receive Medicare benefits without regard to age or other factors.[12] The certitude of payment helped create an industry focused solely on providing care to ESRD sufferers. Although the industry was initially comparatively atomistic (Farley, 1993, Wilson, 2013), by the 21st century it had become extremely concentrated. Most strikingly, the two leading for-profit chains' share of facilities reached almost 60 percent by the end of 2008. This has been achieved through a combination of "organic" growth via the opening of new facilities, and by acquiring other for-profit chains via a series of mergers (Pozniak et al., 2010, Cutler et al., 2012). Unsurprisingly, many of the more recent mergers have drawn scrutiny from antitrust enforcement agencies.[13] Overall, these factors suggest that controlling for the possibility of different impacts from the proximity of facilities under different types of ownership is a potentially important element.

Medicare's de facto monopsonist position has given it tremendous influence on the industry, mainly through asserting minimum quality standards and the establishment of deterministic pricing rules. These pricing rules suggest that competition principally takes place via quality and focusing on costs, and allows one to avoid focusing simultaneously on price and quality competition.[14]

The dominance of just a few for-profit entities has led to considerable scholarship aimed at

[11]For more details on treatment modalities, see `http://www.usrds.org/2012/view/v2_01.aspx`.

[12]Medicare covers approximately 80 percent of treatment costs; patients cover the remainder out of pocket, or through supplemental insurance policies. For in-clinic dialysis, Medicare covers exactly 80 percent. For additional copay information, see, e.g., `http://www.carepathways.com/MedicareCoverage.cfm`.

[13] For example, the Federal Trade Commission (FTC) recently required that DaVita sell off 29 dialysis centers in order to preserve competition in 22 different local markets. See `http://www.ftc.gov/opa/2011/09/davita.shtm`.

[14]For lengthier discussion of payment details, see Wilson (2013) and citations therein. For an analysis of the impact of dialysis provider concentration on private insurers, see Cutler et al. (2012).

understanding the causal impact of both ownership and competition. Despite the high degree of scrutiny, however, there has been little consensus as many papers have reached opposing conclusions. For example, Garg et al. (1999), Devereaux et al. (2002), Zhang et al. (2011), and Grieco and McDevitt (2012) present evidence suggesting that for-profit status is associated with worse outcomes. However, there also have been news stories and scholarly articles noting that dialysis facilities profit heavily from prescribing certain medications (see, e.g., Thamer et al. (2007) or Whoriskey (2012)), which might cause for-profit facilities to systematically seek out sicker patients. Moreover, Brooks et al. (2006) found evidence consistent with this using an IV approach to account for patient heterogeneity. Similarly contradictory results have arisen in studies focusing on competition, with Grieco and McDevitt (2012) suggesting a non-monotonic relationship between quality and competition, Cutler et al. (2012) concluding that there was no relationship at all, and Lee et al. (2010) actually finding a negative relationship between competition and quality.

The inconsistency of the past results may suggest the presence of unaccounted for confounding factors, making the setting an especially appropriate one for applying the CF-model developed above.

3.2 Data

In assessing the influence of market structure and ownership on patient outcomes, this paper relies on data obtained from the United States Renal Dialysis System (USRDS). Part of the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK), the USRDS collects and integrates data taken from a variety of surveys performed by other elements of the National Institutes of Health (NIH), Centers for Medicare and Medicaid Services (CMS), and other governmental agencies. These data are at both the patient and facility level.

The USRDS facility data were also exploited in Wilson (2013), and include information on where factors like where a given facility is located (down to the zipcode level), its ownership status (for-profit, non-profit, and a small number of cases where ownership status is unknown) and whether the

facility is part of a chain.[15] In all cases, the patient-level data provide information on age, gender, race, zipcode of residence, and how long the patient has been receiving dialysis treatment. In an effort to ensure that my results are as robust as possible, I estimate treatment models excluding those who switch treatment routines during a given year.[16]

Within the USRDS data, several different outcome variables are available for use as proxies of facility quality. I focus on the following three: whether or not the patient died during their year of treatment; the number of days the patient was hospitalized for those episodes beginning in the year they received treatment at a given facility; and the number of days the patient spent in the intensive care unit (ICU) or cardiac care unit (CCU) beginning in the year they received treatment at a particular facility. All are factors that have been used as metrics for outcome quality in the past health services and medical literatures on dialysis facility quality (Garg et al., 1999, Ford and Kaserman, 2000, Devereaux et al., 2002, Brooks et al., 2006, Zhang et al., 2011).

In addition to the USRDS data, I also exploit demographic information from the Surveillance, Epidemiology and End Results (SEER) Program, which is also affiliated with the NIH. Since ESRD grows in commonality with age, I follow Wilson (2013) and proxy for local demand for dialysis services using the county population that is over 60. Since zipcodes do not map perfectly to counties, I match each zipcode to the county it was most closely associated with (in terms of population).

In the decomposition stage, one of the key questions of interest is the connection between facility quality and market structure. For my baseline models, I characterize market structure using the (logged) number of competitors within a certain radius. This is consistent with vairous past analyses of competition in retail industries (Shepard, 1993, Hosken et al., 2008). I focus on the number of facilities within 10 miles of the centrum of the zipcode a facility is located within, controlling

[15] As described in Wilson (2013), the facility data are somewhat noisy in regards to ownership status. The approach to cleaning the facility data is described in that paper and below in the appendix. To be considered part of a chain, the USRDS requires that there be at least 20 or more facilities with the same owner. Thus, the number of facilities associated with chains in the data is a conservative estimate of the true number.

[16] See the Appendix for details on the construction of the dataset.

for whether or not the facilities share the same owner as the focal facility. However, as discussed further below, the qualitative findings that this geographic market definition produces are robust to alternative specifications.

Table 1 shows the number of facility-year observations affiliated with each chain in the Atlanta area, while Figure 1 shows a map of the facilities' locations. The Table indicates that the overwhelming majority of facilities are affiliated with either DaVita or Fresenius. Of the chains identified in the USRDS data, only DCI operates as a non-profit. Approximately 55 percent of observations in the sample associated with independents are with for-profit facilities. The Figure suggests that the two large chains' facilities are somewhat less likely to be in the city center.

Table 1: Brands and Ownership Structure of Facilities

Chain	**Obs**	**Percent**
Davita	7,247	29.06
DCI	1,048	4.2
Fresenius	6,261	25.1
Gambro	1,550	6.21
NRA	177	0.71
NRI	440	1.76
RCG	264	1.06
Independent	7,953	31.89
Total	24,940	100

3.3 Descriptive Analysis

As noted above, in order to appropriately estimate the choice model, rules must be established for which facilities belong in each patient's choice set. An examination of the data shows that 93 percent of patients in the sample receive treatment within 20 miles of their home; 86 percent do so within 15 miles; and 71 percent receive care within 10 miles. Therefore, I define patients' choice sets as the larger of the set of facilities within 15 miles of their home zipcode, if they choose a facility within that radius, or all of the facilities within the radius of their chosen facility.[17]

[17]Preliminary work with alternative rules led to similar findings.

Table 2 shows descriptive statistics at the facility level. Summary values are shown for the entire sample as well as stratified by ownership status. In addition to considering factors like the average number of patients seen and the average population over 60 in the facility's county, I also include measures for the degree of competitiveness and concentration in their area. Overall, the Table shows quite striking differences depending on ownership status. Non-profit facilities tend to be in more competitively congested areas. Indeed, the average number of facilities within a 10 mile radius of the centrum of a non-profit facility's zipcode is three times as high as that for a for-profit facility. This can be at least partially explained by the fact that non-profits tend to be located in counties more densely populated with the older Americans who are most prone to suffering from ESRD. Relatedly, the average non-profit facility sees many more patients than the average for-profit one.

Table 2: Variation in Facility Characteristics Across Ownership Types

	Total			**For-profit**			**Non-profit**			
	Obs	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**T-Stat**
Nearby Facilities	436	15.01	12.69	399	13.72	12.15	31	28.23	10.64	-7.23
Same Owner	436	3.40	4.94	399	3.60	5.10	31	1.45	1.52	5.75
Different Owner	436	11.61	10.37	399	10.12	9.13	31	26.77	10.01	-8.98
Facility Age	436	11.40	8.38	399	10.38	7.62	31	23.39	8.68	-8.11
Population > 60	436	67506	41912	399	65246	41974	31	92192	35781	-3.99
Patients	436	279.55	316.67	399	247.40	135.63	31	667.81	1016.46	-2.30

Table 3 shows descriptive statistics at the patient level for the entire sample as well as for those patients frequenting for-profit and non-profit facilities.[18] Intuitively given the evolution of the industry, a large majority of patients receive care at for-profit facilities. Somewhat less intuitively, the Table indicates quite dramatic differences in the average patient seen across ownership forms. The average non-profit patient is much more likely to be male, black, and a longterm sufferer of ESRD. Although not shown here, an analysis of the subset of data that include patients' comorbidities indicates that non-profits' patients are also more likely to self-report being a smoker and/or dependent upon alchohol. Some of these factors are typically considered risk factors. However, for-profit patients also have some characteristics typically associated with worse health outcomes. In

[18] I do not provide summary values for the small number of patients frequenting facilities whose ownership status is not known in the data.

particular, they are more likely to be older and report suffering from diabetes.

Table 3: Variation in Patient Characteristics Across Ownership Types

	Total			For-profit			Non-profit			
	Obs	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**T-Stat**
Male	24940	0.54	0.50	20326	0.52	0.50	4129	0.57	0.50	-5.23
Black	24940	0.67	0.47	20326	0.62	0.49	4129	0.88	0.33	-41.41
White	24940	0.29	0.46	20326	0.34	0.47	4129	0.08	0.27	49.01
Age	24940	5.84	1.53	20326	5.95	1.51	4129	5.25	1.55	26.67
Length of Treatment	24940	0.35	0.40	20326	0.33	0.39	4129	0.44	0.47	-14.00
Died	24940	0.15	0.36	20326	0.15	0.36	4129	0.13	0.34	2.81
Days in ICU/CCU	24940	2.82	7.90	20326	3.01	8.21	4129	1.99	6.32	8.97
Days in hospital	24940	9.79	20.38	20326	10.41	21.20	4129	7.28	16.28	10.65

Focusing on patient outcomes, Table 3 suggests that the average outcome for patients at non-profit facilities is superior to that for patients at for-profit facilities. Average mortality is 12 percent lower, the number of days in either the CCU or ICU is 33 percent lower, and the number of days hospitalized overall is 25 percent lower. These simple statistics would appear consistent with the conventional expectation that non-profits provide higher quality, which – as noted above – many past analyses of the dialysis sector have also found. However, the differences in the average patient described above suggest that some of the differences could in fact be at least partially attributed to for-profit facilities systematically seeking out sicker patients. In which case, for-profits' average performance may only look worse before controlling for patient severity. As also noted above, there are some grounds for thinking this might be true.

All of this suggests that it is quite important to control for the possibility of systemmatic selection of treating facility before making any conclusions. Therefore, I now turn to more formal methods of inferring the impact of different facility and market characteristics on treatment quality.

4 Does Patient Selection Matter?

For each of the three outcome variables – mortality, the (logged) days of "serious" hospitalization, and the (logged) overall number of days hospitalized, I estimate OLS, facility FE, IV, and CF

models. In other words, I estimate linear versions of Equation (2) for these outcomes, dealing with the possibility of heterogeneous coefficients in different ways.

As discussed above, the IV and CF models both rely on a first stage conditional logit model of the likelihood that a given patient chooses a given facility.[19] The choice models include facility fixed effects as well as a quadratic function of distance, the interaction of distance with patient age, the interaction of years of hemodialysis treatment with distance, and the interaction between the disease causing the patient's ESRD and the size of the facility (in terms of dialysis stations). All of the distance terms – which are the excluded variables in the outcome models – are precisely identified and of reasonable sign. The coefficient estimates for the choice model can be found in Table B-1 in the Appendix.

Tables 4, 5, and 6 show the effects of the patient-level variables on mortality, the number of days in the ICU or CCU, and total number of days hospitalized, respectively. To address the likelihood of irregular standard errors, I bootstrap, stratifying by facility. The resulting estimates for the impact of most of the various patient-level factors are all of reasonable signs and economic magnitude. Moreover, they are broadly consistent with the prior literature. For example, I find that older, male, and white individuals tend to have more negative health outcomes.

More interestingly, although of relatively small absolute magnitude, the differences in estimated coefficients across models are of non-trivial economic importance. For example, the 0.03 difference in the IV and CF coefficients on white in the mortality model is equivalent to 20 percent of the unconditional likelihood of death. The changes in patient characteristic coefficients across models is consistent with the hypothesis that different facilities may target, or be viewed especially favorably by, different groups. Overall, I consistently find that the statistical precision of the disease-related factors is much less for the IV and CF models. This may indicate that these factors play heavily into patients' selection of different facilities, and that once modeled in the choice of treating location, they no longer are as consistently meaningful in their own right. Moreover, the existence of substan-

[19] To be clear, for the IV model, I simply replace the endogenous variables with the predicted likelihood of choosing each facility.

Table 4: Model of Treatment Outcomes: Mortality

	OLS b/se	**FE** b/se	**IV** b/se	**CF** b/se
Age	-0.060***	-0.066***	-0.059***	-0.068***
	0.008	0.009	0.008	0.009
Age^2	0.008***	0.009***	0.008***	0.009***
	0.001	0.001	0.001	0.001
Years Treated	-0.097***	-0.096***	-0.102***	-0.098***
	0.02	0.02	0.021	0.021
Age*Years Treated	0.028***	0.028***	0.028***	0.029***
	0.004	0.004	0.004	0.004
Male	0.008	0.007	0.007	0.006
	0.005	0.005	0.005	0.005
Black	0.001	-0.001	-0.003	-0.007
	0.011	0.012	0.012	0.013
White	0.039***	0.044***	0.041***	0.038***
	0.011	0.011	0.012	0.012
Diabetes	0.194***	0.185***	0.242	0.14
	0.027	0.054	0.241	0.41
Hypertension	0.161***	0.149**	0.196	0.107
	0.027	0.054	0.242	0.41
Glomeruloneph	0.141***	0.134*	0.16	0.075
	0.027	0.054	0.24	0.408
Cystic Kidney	0.119***	0.114*	0.142	0.058
	0.032	0.054	0.239	0.411
Other Urologic	0.138***	0.132*	0.157	0.075
	0.03	0.056	0.242	0.413
Other Cause	0.225***	0.218***	0.241	0.158
	0.025	0.054	0.238	0.408
Unknown Cause	0.178***	0.171**	0.199	0.109
	0.027	0.054	0.242	0.409
Missing	0.225*	0.213	0.269	0.189
	0.111	0.113	0.277	0.416
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24940	24940	24940	24940
r2	0.193	0.197	0.197	0.204
r2_a	0.191	0.192	0.192	0.193

* p<0.10, ** p<0.05, *** p<0.01. All standard errors were bootstrapped, stratifying by facility. The model was estimated without a constant, and there was no excluded disease category. The excluded racial category is all races other than white or black.

Table 5: Model of Treatment Outcomes: (Logged) Days in ICU/CCU

	OLS b/se	**FE** b/se	**IV** b/se	**CF** b/se
Age	-0.002	0.044	0	0.037
	0.022	0.023	0.023	0.024
Age^2	0.011***	0.007***	0.011***	0.008***
	0.002	0.002	0.002	0.002
Years Treated	0.593***	0.596***	0.594***	0.573***
	0.065	0.065	0.066	0.068
Age*Years Treated	-0.098***	-0.096***	-0.099***	-0.091***
	0.012	0.012	0.012	0.012
Male	-0.031**	-0.023*	-0.029**	-0.025*
	0.011	0.011	0.011	0.011
Black	0.153***	0.158***	0.140***	0.154***
	0.024	0.025	0.024	0.025
White	0.203***	0.228***	0.202***	0.227***
	0.027	0.027	0.025	0.027
Diabetes	-0.405***	-0.438**	0.418	-1.712
	0.077	0.151	0.716	1.003
Hypertension	-0.478***	-0.521***	0.338	-1.791
	0.073	0.149	0.719	1.004
Glomeruloneph	-0.506***	-0.515***	0.275	-1.8
	0.073	0.148	0.723	1.002
Cystic Kidney	-0.648***	-0.685***	0.141	-1.968
	0.075	0.154	0.715	1.011
Other Urologic	-0.554***	-0.589***	0.213	-1.871
	0.077	0.162	0.713	1.004
Other Cause	-0.426***	-0.453**	0.347	-1.738
	0.073	0.154	0.712	0.999
Unknown Cause	-0.461***	-0.479**	0.332	-1.777
	0.08	0.152	0.72	1.003
Missing	-0.533	-0.607	0.258	-1.832
	0.327	0.335	0.863	1.036
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24940	24940	24940	24940
r2	0.285	0.299	0.292	0.307
r2_a	0.284	0.295	0.288	0.298

* p<0.10, ** p<0.05, *** p<0.01. All standard errors were bootstrapped, stratifying by facility. The model was estimated without a constant, and there was no excluded disease category. The excluded racial category is all races other than white or black.

Table 6: Model of Treatment Outcomes: (Logged) Days Hospitalized

	OLS b/se	**FE** b/se	**IV** b/se	**CF** b/se
Age	-0.084*	-0.038	-0.076*	-0.045
	0.035	0.039	0.036	0.039
Age^2	0.026***	0.022***	0.025***	0.022***
	0.003	0.003	0.003	0.003
Years Treated	1.316***	1.285***	1.315***	1.252***
	0.093	0.094	0.092	0.095
Age*Years Treated	-0.197***	-0.189***	-0.198***	-0.182***
	0.017	0.017	0.017	0.017
Male	-0.107***	-0.081***	-0.108***	-0.083***
	0.017	0.018	0.017	0.018
Black	0.441***	0.422***	0.410***	0.407***
	0.039	0.039	0.037	0.039
White	0.535***	0.557***	0.533***	0.543***
	0.04	0.041	0.04	0.043
Diabetes	-0.740***	-0.562**	-0.264	-1.121
	0.113	0.214	0.838	1.274
Hypertension	-0.951***	-0.787***	-0.499	-1.345
	0.105	0.209	0.841	1.278
Glomeruloneph	-0.943***	-0.733***	-0.464	-1.282
	0.107	0.209	0.845	1.267
Cystic Kidney	-1.083***	-0.896***	-0.587	-1.44
	0.11	0.215	0.841	1.286
Other Urologic	-1.092***	-0.897***	-0.614	-1.441
	0.115	0.242	0.846	1.266
Other Cause	-0.799***	-0.605**	-0.325	-1.155
	0.113	0.218	0.835	1.267
Unknown Cause	-0.962***	-0.736***	-0.464	-1.299
	0.112	0.21	0.834	1.269
Missing	-0.721	-0.62	-0.244	-1.11
	0.518	0.472	1.059	1.268
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24940	24940	24940	24940
r2	0.468	0.477	0.472	0.484
r2_a	0.467	0.474	0.469	0.477

* p<0.10, ** p<0.05, *** p<0.01. All standard errors were bootstrapped, stratifying by facility. The model was estimated without a constant, and there was no excluded disease category. The excluded racial category is all races other than white or black.

tial differences across models suggests that the CF models, with their less stringent assumptions, are preferable.

The potential importance of conscious selection can also be seen in a variety of other ways. First, it would imply substantial variation in the facility-level quality estimates, which is what I observe in the data. Some sense of the magnitude of the differences across methods can be seen in Figure 2, which shows scatter plots of the facility quality estimates for the number days in the ICU/CCU quality for the CF model compared to the to the IV and FE models.[20] The figures indicate that the methods that account for selection produce substantially more dispersed estimates than the FE model. Moreover, the importance of controlling for selection can be seen in the fact that facilities' estimated quality effects are surprisingly uncorrelated as seen in both the Figures and Table 7, which shows the correlation matrix for all of the different facility quality estimates. Within estimation method, facilities' estimated qualities tend to be fairly correlated. However, there is very little relation across estimation methods.[21]

Table 7: Correlation Matrix for Quality Estimates

	D-FE	D-IV	D-CF	E-FE	E-IV	E-CF	S-FE	S-IV	S-CF
D-FE	1.00								
D-IV	0.09	1.00							
D-CF	0.11	0.20	1.00						
E-FE	0.40	0.15	0.02	1.00					
E-IV	0.09	0.99	0.21	0.15	1.00				
E-CF	0.00	0.11	0.32	0.15	0.10	1.00			
S-FE	0.48	0.11	-0.09	0.73	0.10	0.03	1.00		
S-IV	0.09	0.98	0.21	0.16	1.00	0.11	0.10	1.00	
S-CF	0.11	0.24	0.64	0.22	0.25	0.68	0.03	0.25	1.00

D represents mortality models, S represents days in the ICU/CCU, and E represents days in the hospital.

Not only do different estimation approaches produce observably estimates different, but tradi-

[20]The IV quality estimates were extremely dispersed. For ease of viewing, I limited the focus to those whose absolute value was less than 20. Scatter plots for the other outcome variables are qualitatively similar and available upon request.

[21]The Table clearly shows that the IV estimates are extremely closely correlated. Upon investigation, I found that this appears driven by the presence of common outliers across outcome variables. When I restrict consideration to estimates between the 10th and 90th percentiles, I find correlation coefficients that are less strikingly high and of similar magnitudes to those of the other estimation methods.

tional specification choice metrics consistently indicate that the CF models are preferable to more parsimonious alternatives.[22] For example, Tables 4, 5, and 6 show that using the adjusted R^2 metric, the CF models do a better job of fitting the data, even adjusting for their much higher number of included regressors. This remains true when information criteria that more heavily penalize overfitting are used (Liu et al., 2010). As can be seen in Table B-2 in the Appendix, which shows the Akaike information criterion for each of the models.[23] Moreover, following Petrin and Train (2010), I perform Wald tests of the joint insignificance of the control function elements and find that the null is rejected at the 1 percent level for all models.

As a final, but perhaps most important test, it is worth considering whether the coefficient estimates on the interaction terms in the control function make intuitive sense. As discussed above, these terms capture the relationship between the heterogeneous impact of receiving treatment at a given location, and the choice to receive treatment there. Since outcomes are negative in these models, one would expect to find negative coefficients on the interaction terms. This would show that if patients' were highly unlikely to choose a given treating facility, yet ended up receiving treatment there, the choice would be associated with lower expected mortality, fewer days in the ICU/CCU, and/or less days hospitalized. Although the individual estimated coefficients are heterogeous, summary statistics of the estimates show that they are negative on average. Moreover, across all outcome variables, the magnitude of the average effect is greater if one weights by relative statistical precision (in this case, the inverse of the coefficient of variation).

Overall, the evidence from the different treatment models lends support to the idea of selection based not just on condition severity but also heterogeneous response to treatments. However, the question of the practical importance of accounting for such endogeneity when considering the relationship between market structure and quality remains.

[22] I explored whether Hausman tests could be used to draw inferences about the appropriateness of the different metrics. Unfortunately, though not surprisingly, the tests results were not well-defined, and thus cannot be used to infer anything about the appropriateness of the different models (Small and Hsiao, 1985).

[23] This also remains true when I use information criteria that prefer even more parsimonious models. Details are available upon request.

5 What Determines Facility Quality?

To explore the practical implications of conscious facility selection on the relationship between market structure and mean quality, Table 8 shows decompositions of the different quality estimates on simple proxies for market structure and organizational characteristics. Because of the small number of observations, I use a very parsimonious set of regressors. Broadly in keeping with Davis (2006) and Berry (1992), I account for market structure using the logged sums of facilities affiliated with the same owner and with different owners. I also include a binary indicator for whether or not the facility has non-profit status, and a limited set of chain identifiers that account for the possibility that Davita and/or Fresenius behave differently than the mass of all other facilities.[24]

Columns 1-3 of Tables 8 show the different estimates of quality from the mortality models; Columns 4-6 show the results for the number of days in the ICU or CCU; and Columns 7-9 show the results for the total number of days hospitalized. In each "triad," the first column uses the quality estimates from a FE model that effectively takes patient choices as predetermined. The second column uses the IV quality estimates, and the third column exploits the CF results. The facility level observations are weighted to take account of the fact that quality estimates for more populous facilities reflect the mean outcome for more patients as well as being more likely to be precisely estimated.[25] In all cases, the standard errors are robust to heteroskedasticity.[26]

Focusing on the CF estimates, Table 8 tells a very consistent story about the relationship between quality and competition. As the number of nearby facilities under the same ownership increases, the facility's mean quality declines by a statistically and economically significant amount for all three outcome metrics. For example, in response to a one unit increase in the log number of

[24]For the time being, I do not specify which chain effect estimate is for which chain.

[25]As suggested in Solon et al. (2013), I explored the sensitivity of the results to alternative weighting approaches – such as not weighting or even weighting by the inverse of the number of patients seen – and found that they generally produce broadly similar results. The chief point of difference is that no impact from market structure on days hospitalized is found for the market structure variables when I use "inverse" weighting. Details are available upon request.

[26]The importance of outliers in the IV models is immediately apparent from the estimates, which are implausibly large. Winsorized models produce results with the same signs but magnitudes broadly comparable to those in the CF and FE models.

affiliated outlets (approximately equal to one standard deviation), the expected incidence of death would increase 30 percentage points. That is a very considerable impact. Similarly, a 10 percent increase in the number of associated facilities would be linked to greater than 10 percent increases in the expected days in the ICU or CCU, and greater than 15 percent increases in the number of days hospitalized. Moreover, for all three metrics, the nearby presence of facilities under different ownership is associated with quality improvements, albeit not statistically significantly so. Figure 3 shows a map of the mortality quality estimates, and – in connection with Figure 1 – is broadly consistent with the regression estimates.

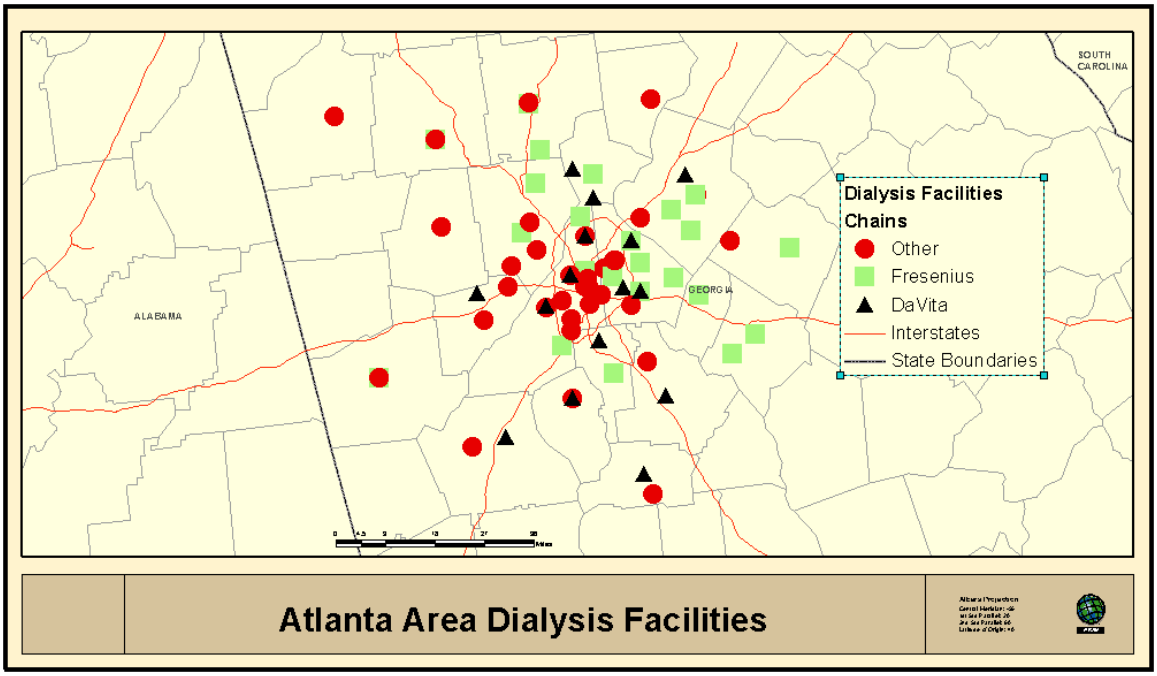
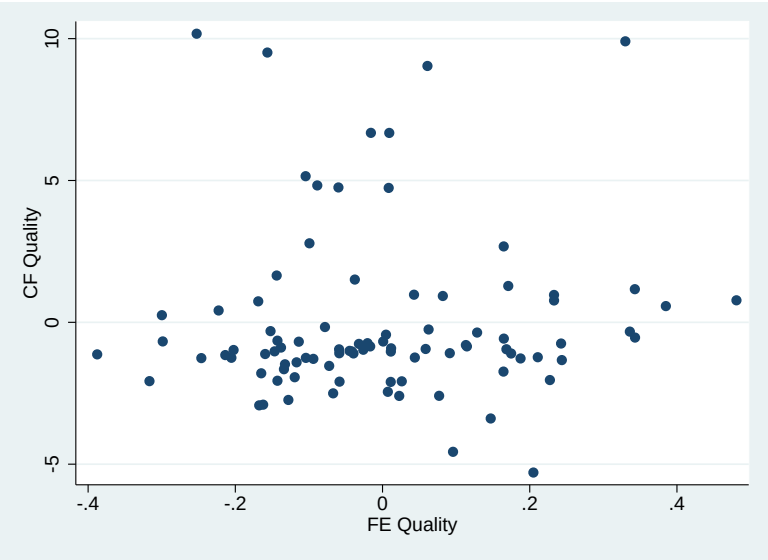
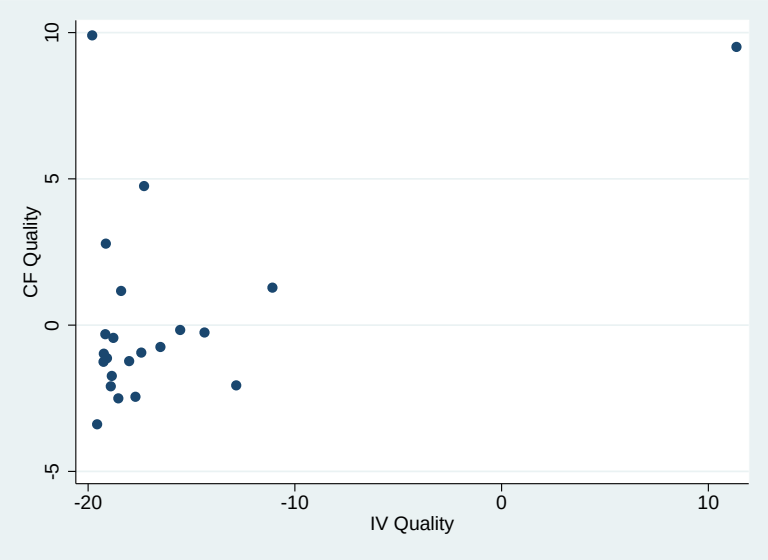


Figure 1: Chain Locations



(a) FE vs. CF



(b) IV vs. CF

Figure 2: Comparison of Facility Effects on Days in CCU/ICU.

Table 8: Decomposition of Facility Quality on Market and Facility Characteristics

	Mortality			Days in ICU/CCU			Days Hospitalized		
	FE	IV	CF	FE	IV	CF	FE	IV	CF
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Log(Same Owner +1)	-0.006	-110.459+	0.303+	-0.058*	-105.024	1.189**	0.036	-143.36	1.528**
	0.006	84.58	0.218	0.03	95.629	0.595	0.039	127.193	0.746
Log(Different + 1)	0.003	92.385+	-0.034	0.013	91.802	-0.141	0.002	124.562+	-0.161
	0.004	64.412	0.13	0.023	72.012	0.414	0.032	96.176	0.483
Facility Age	0	-1.456	-0.007	0.001	-2.954	-0.031	-0.001	-3.732	-0.03
	0	2.903	0.006	0.002	2.963	0.026	0.003	4.028	0.034
Non-Profit	-0.008	-135.322+	0.485	-0.143*	-87.058	1.848+	-0.195*	-125.235	2.372+
	0.012	95.895	0.424	0.075	92.113	1.316	0.099	127.296	1.81
Alternative Large Firm	-0.01	136.637	0.303*	-0.042	155.303	0.545	-0.046	207.111	0.23
	0.009	120.392	0.176	0.049	138.771	0.631	0.064	184.14	0.69
Other	-0.002	-37.216	0.433	0.004	-58.283	1.574*	0.130+	-78.385	1.706+
	0.013	52.038	0.339	0.071	56.786	0.822	0.085	76.605	1.053
N	92	90	92	92	90	92	92	90	92
r2	0.054	0.06	0.104	0.103	0.051	0.132	0.146	0.052	0.168
r2_a	-0.012	-0.008	0.04	0.04	-0.018	0.071	0.086	-0.017	0.109

* p<0.10, ** p<0.05, *** p<0.01, + p< 0.10 in one-sided test. Standard errors robust to heteroskedasticity.

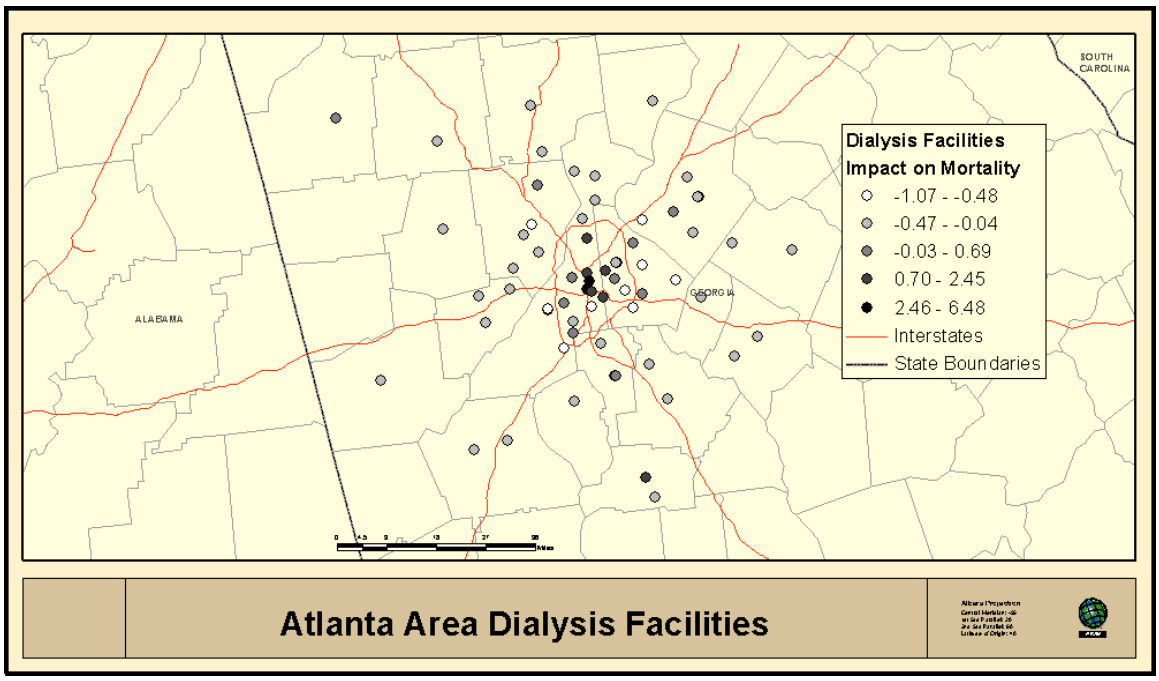


Figure 3: Mortality Quality

In addition to suggesting a negative relationship between quality and concentration, which is strongly consistent with the economic theory (Gaynor, 2006), the results demonstrate the importance of accounting for conscious patient selection. Models using quality estimates generated by IV or FE regressions not only do not capture the true magnitude of competition on facilities' mean quality, but actually tend to miss its qualitative impact. This can be seen in the fact that five out of six of the non-CF models produce estimates that would positively – though perhaps weakly – associate quality with concentration. This is consistent with the general concern about some simultaneity between the dependent and independent variables in market structure models. In other words, the results are consistent with the concern that facilities that specialize in, or target, certain types of patients would be more likely to open where those patients are present. However, if under the same ownership, they might not have the same incentive to invest in upping their overall quality.

Although in line with many – though not all – papers on hospital competition (Gaynor and Town, 2011), my finding that competition generally fosters average quality is not consistent with either of the most recent economic papers on the dialysis industry. As noted above, Grieco and

McDevitt (2012) find a non-monotonic relationship between competition and average quality, with monopolists providing the highest quality of care. I believe that our disparate findings can be reconciled in two ways. First, Grieco and McDevitt (2012) make the implicit assumption – perhaps as a result of data limitations – that all facilities compete on equal grounds, whereas I accomodate the existence and substantial importance of chains, allowing for facilities affiliated with the same chain to have different impacts than those affiliated with other owners. When I estimate models that treat all facilities equally, I am able to produce more qualitatively similar results to theirs insofar as I find that average quality deteriorates in the presence of additional outlets. This can be seen in Table B-3 in the Appendix. Second, the metric that Grieco and McDevitt (2012) use for quality is "raw," and if their non-parametric function of those factors affecting production does not fully account for patients' selection process, then their estimates of the impact of market structure may not be unbiased.

The other recent paper assessing quality in the dialysis sector – Cutler et al. (2012) – finds no connection between concentration and patient care while their usage of mergers likely leads to plausibly exogenous variation, one might wonder whether it relies on variation that is "too local" to pick up on the relationship identified here. Moreover, their quality metric may be "contaminated" by selection effects, which may make it harder to identify the impact of changes in competition.

In addition to my results' implications for the relationship between average quality and competition, the decomposition of the CF estimates of quality suggest that the average quality of non-profit facilities may be inferior to that of for-profit facilities. However, this inference should be approached with caution given the very small number of non-profit facilities within the data. Nevertheless, this raises interesting questions about evaluating the role of profit status in care provision insofar as most prior work implies that for-profit facilities are more efficient (Held and Pauly, 1983, Grieco and McDevitt, 2012, Wilson, 2013). If the results for the Atlanta area generalize to the nation as a whole, then it would appear that the rise of for-profits may have been more welfare increasing than usually expected.

Somewhat interestingly, I find that older facilities tend to provide better care even after accounting for patient selection. This may reflect the fact that newer facilities may still be learning. Alternatively, they may reflect the fact that as demand for dialyzation steadily grows, the supply of quality clinicians is getting stretched ever thinner, and newer facilities have to hire inexperienced staff.

Overall, the results of my decomposition of the CF facility quality estimates strongly support the mainstream opinion of economists that competition is positively associated with treatment quality (Gaynor and Town, 2011). Moreover, I found this result robust to alternative specifications, which can be seen in Tables B-4 and B-5 in the Appendix, which show the results of models where observations are not weighted, the market structure variables are replaced with level measures normalized by the county population over 60, and simple non-parametric estimates. Across all of these different models, I find remarkably similar qualitative results.[27]

6 Conclusion

In this paper, I focus on how selection concerns complicate health outcome modeling. To address this problem, I develop an econometric approach using a control function that addresses not only the standard concern about unobservable variation in condition severity but also heterogeneous response to treatment. The modeling framework is then applied to dialysis patient data from the USRDS. Specification tests suggest that not only is "traditional" selection a significant problem in identifying the average quality of different facilities, but so too is patients' heterogeneous responsiveness to treatment. Decomposing the estimates of treatment facility quality obtained from the control function model, I find evidence consistent with the hypothesis that competition fosters higher quality care. I also find some evidence that for-profit facilities' average quality of care is

[27] In addition, I experimented with adding additional controls for whether a given facility had an affiliation with a hospital. As discussed in Wilson (2013), this variable's meaning in the data is not entirely clear. It could indicate that the treating facility is part of a hospital complex or that it shares some financial affiliation with a hospital. In any case, when included, the variable tends not to have the sign one would expect if hospital-affiliation induced excessive hospitalization. Depending on the specification and weighting scheme, the inclusion of the variable sometimes changed the significance of the shared ownership variable.

higher.

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A Dataset Construction

Facility Data

I follow the same data cleaning procedures as in Wilson (2013). As described in that paper, the USRDS data on yearly facility characteristics and activities are contained in the FACILITY dataset. Examining the connection between profit-status and chain affiliation in these data, it became evident that the raw USRDS data contained errors. In reality, all of the chains are universally either for- or non-profit. However, a non-trivial number of observations assign the "wrong" profit status to a facility affiliated with a given chain. Upon investigation, I came to the conclusion that much of the problem stemmed from lags in updating a given facility's status following a change in ownership. As a result, I imposed that a facility's for-profit status should match its chain affiliation.

The USRDS (2011) also warn that when a facility changes hands its identification number may also change. Thus, a facility would be seen to exit that did was not really liquidated, while another facility would appear to enter, though it would in truth be using old equipment and staff. Exploration of the data indicates that such events are uncommon insofar as most facilities known to be acquired remain in the data.

More commonly, I found that the data were sometimes slow to account for mergers. I addressed this problem by relying on the merger history provided in Cutler et al. (2012), imposing that facilities' affiliation should reflect whichever chain owned it for the bulk of the calendar year. In the econometric analyses, any noise introduced by erroneous cleaning should make it more difficult to cleanly identify differences across for- and non-profit facilities, and hence is a conservative approach.

Patient Data

The USRDS' patient-level data is spread across multiple different files, each focusing on different elements of potential interest. I constructed the data used in this paper as follows.

Patients' treatment history data – which are contained in RXHIST60 – are stratified by treatment modality and treating facility. Each distinct spell has a start and stop date. I merged these data with patients' time varying residence information – which is contained in RESIDENC – after limiting the residential information to places in Georgia. I further limited the data to individuals who moved more than three times within a given treatment regime. The concern is that such moves might indicate that the person was suffering from something unobservable that might make them an unrepresentative subject. This affected few patients. Subsequently, I merged the patient-treatment spell-residence information to the facility-year data. I then dropped all observations corresponding to treatment modalities other than hemodialysis received in facilitlies. I also excluded those individuals who shifted facilities within a year. Again, the concern is that the shift could be correlated with something outside of treatment, which it would be inappropriate to allow to be linked to the quality of treatment provided by either facility.

I subsequently merged in information on comorbidities – found in the MEDEVID dataset – and patient demographics – found in PATIENTS. From this information, I constructed a yearly measure of age by subtracting patients' birthyear from the current year.

Facilities – and the patients associated with them – were dropped if they did not perform 520 hemodialysis treatments in a year. I also focused only on those patients living in the zipcodes associated with the counties in the MSA according to the U.S. Census' Population Division.

Distance Data

Distances between places were constructed by the "Great Circle" method using the latitude and longitude centrums associated with zipcodes. The primary source of this information was the U.S. Census' ZCTA5 dataset. As zipcodes do not map perfectly to ZCTAs, some zipcodes in the data were not present in the ZCTA dataset. I used the information available at `brainyzip.com` to fill in these missing values.

Sample Construction

I initially mapped all of the facilities within the Atlanta MSA to all of the patients. Then as discussed in the text, I dropped the smaller of the set of observations further away than the chosen facility or the set of facilities further than 15 miles from the patients' zipcode of residence. I also dropped those facilities were not chosen by at least 50 patients over the course of the sample period. Eyeball checks indicate that – consistent with intuition – these facilities were in rural areas on the very outskirts of the Atlanta MSA.

Before estimating the patient-outcome models, I found it necessary to again thin the data, dropping observations associated with facilities with fewer than 60 patient outcomes.

Further details are available upon request.

B Additional Tables

Table B-1: Choice Model Estimates

	b/se
Distance	-0.437***
	0.008
Distance^2	0.022***
	0
Distance*Length of Treatment	0.003***
	0
Distance*Age	-0.001***
	0
Distance*1(Diabetes)	0.025***
	0.006
Distance*1(Hypertension)	0.028***
	0.006
Distance*1(Other Causes)	0.004
	0.007
N	720314

* p<0.10, ** p<0.05, *** p<0.01.

Table B-2: AIC Results

	Model			
Outcome	**OLS**	**FE**	**IV**	**CF**
Mortality	17922	17806	17807	17590
Log (Days in ICU/CCU)	69518	69027	69292	68741
Log (Days Hospitalized)	87319	86876	87118	86568

Table B-3: Results for Model without Controls for Ownership

	Mortality CF b/se	**Days in ICU/CCU CF b/se**	**Days Hospitalized CF b/se**
Nearby Facilities	0.122*	0.491*	0.653**
	0.071	0.269	0.274
Facility Age	-0.005	-0.026	-0.023
	0.006	0.023	0.032
Non-Profit	0.233	0.837	1.073
	0.326	1.219	1.706
Alternative Large Firm	0.187+	0.101	-0.338
	0.142	0.619	0.645
Other	0.072	0.168	-0.093
	0.146	0.481	0.58
N	92	92	92
r2	0.052	0.068	0.093
r2_a	-0.003	0.014	0.04

* p<0.10, ** p<0.05, *** p<0.01, + p< 0.10 in one-sided test. Standard errors robust to heteroskedasticity. Observations weighted by number of patients.

Table B-4: Results for Unweighted and Population-Weighted Competition Models

	Unweighted Logs			**Weighted Level / Pop > 60**		
	Mortality CF b/se	**ICU/CCU CF b/se**	**Hospitalized CF b/se**	**Mortality CF b/se**	**ICU/CCU CF b/se**	**Hospitalized CF b/se**
Same	0.489+	1.165*	0.547	0.206	1.254+	1.568*
	0.334	0.65	0.602	0.253	0.822	0.847
Other	-0.049	0.104	0.389	0.031	-0.053	-0.115
	0.138	0.407	0.424	0.091	0.323	0.316
Facility Age	-0.012	-0.028	0.022	-0.004	-0.024	-0.021
	0.011	0.034	0.04	0.006	0.023	0.031
Non-Profit	0.711	2.904*	4.191*	0.347	1.603	2.145
	0.585	1.644	2.248	0.385	1.331	1.852
Alternative Large Firm	0.338	0.361	-0.488	0.233+	0.401	-0.016
	0.266	0.743	0.724	0.158	0.573	0.651
Other	0.708	1.312	-0.013	0.178	0.919+	0.827
	0.597	1.03	0.915	0.262	0.649	0.734
N	92	92	92	92	92	92
r2	0.159	0.18	0.226	0.043	0.065	0.084
r2_a	0.1	0.123	0.171	-0.024	-0.001	0.019

* p<0.10, ** p<0.05, *** p<0.01, + p< 0.10 in one-sided test. Standard errors robust to heteroskedasticity.

Table B-5: Results for Weighted Non-Parametric Model

	Mortality CF b/se	**Days in ICU/CCU CF b/se**	**Days Hospitalized CF b/se**
1(1 same)	0.288	1.056*	1.894**
	0.229	0.56	0.874
1(2 same)	0.37	1.472+	2.194*
	0.365	0.914	1.233
1(3+ same)	0.763*	2.676**	3.445**
	0.425	0.996	1.339
1(1 other)	0.187+	0.419+	0.591*
	0.118	0.27	0.355
1(2 other)	-0.043	-0.222	-0.045
	0.158	0.404	0.492
1(3 other)	-0.07	-0.392	-0.079
	0.315	1.035	1.222
1(4+ other)	-0.124	-0.485	-0.279
	0.174	0.447	0.646
Non-Profit	0.329	1.1	1.687
	0.325	0.931	1.417
Alternative Large Firm	0.145	-0.101	-0.634
	0.179	0.743	0.805
Other	0.475+	1.584**	1.675*
	0.293	0.771	0.991
N	92	92	92
r2	0.153	0.163	0.206
r2_a	0.049	0.06	0.108

* p<0.10, ** p<0.05, *** p<0.01, + p< 0.10 in one-sided test. Standard errors robust to heteroskedasticity. Observations weighted by number of patients.