Quality Transparency and Healthcare Competition*

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Abstract: Transparency about the quality of goods and services offered by firms improves consumer decisions; however, it also informs competitors. We study how competitors respond to increased quality transparency by exploiting a regulatory change that mandates disclosure of quality for all kidney dialysis facilities in the United States. We find that improved quality transparency increases the likelihood of new entry nearby low-quality incumbents. It also increases the sensitivity of demand to quality, reflected in a drop in patient referrals to lower-quality incumbents. Finally, enhanced transparency, via its effect on competition, improves the incumbents' quality of care, as evidenced by reduced hospitalizations and increased investments in skilled labor.

Keywords: Healthcare; dialysis treatment; competition; transparency

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1 Introduction

Competition in healthcare markets has been a prominent goal of policymakers in most developed countries (Katz, 2013). In the United States, several regulators, including the Centers for Medicare and Medicaid Services (CMS) and Federal Trade Commission (FTC), devote considerable resources to promoting competitive healthcare practices.[1] Nevertheless, healthcare markets remain far from being (highly) competitive (e.g., Dranove and Satterthwaite, 2000; Eliason et al., 2020; Wollmann, 2021). Reasons for the lack of competition include inelastic demand for medical services, complex regulations, geographical constraints, and a lack of transparency. Transparency about healthcare quality is a particularly pressing issue since healthcare prices are often regulated and hence quality is the primary dimension along which healthcare providers compete on. Because healthcare quality is not directly observable even *ex post*, this leads to a lack of competitive pressure and quality shirking (e.g., Katz, 2013; Einav et al., 2021).

We use a recent regulatory change to study how transparency about private healthcare providers' quality affects competition from their rivals and, ultimately, healthcare quality. Given the historical lack of healthcare quality transparency (Rao et al., 2021), healthcare regulators have increasingly turned to public disclosure with an aim to inform patients, doctors, and *competitors*. However, the effect of transparency programs on competition and, even more so, on subsequent healthcare quality remains an open question. Prior work on transparency regulation primarily focuses on the disciplinary effects of disclosures on the disclosing party (e.g., Dranove et al., 2003a; Jin and Leslie, 2003; Christensen et al., 2017; Johnson, 2020).[2] In contrast, we study whether disclosure benefits consumers by incentivizing competitors to act on publicly revealed information about quality. In theory, the effect of disclosure requirements on healthcare quality is not obvious *ex ante* as quality competition need not lead to increased quality in a heavily regulated industry (Katz, 2013; Moscelli et al., 2021).

We focus on the US outpatient kidney dialysis sector, which provides an ideal setting to study how quality transparency affects competition. First, it absorbs more than 6 percent of total Medicare spending, representing over 1 percent of the total US Federal Budget.[3] In 2017 alone, this sector treated 458,000 patients at over 7,000 privately-run facilities at a cost exceeding $27 billion. Second, dialysis providers do not compete on price because Medicare covers the vast majority of dialysis patients and pays providers a uniform reimbursement

[1] See, e.g., https://www.ftc.gov/tips-advice/competition-guidance/industry-guidance/health-care.

[2] An important stream of research studies measures of product or service quality—such as rankings, ratings, and scores—in facilitating consumers' decisions (e.g., Pope, 2009; Dranove and Jin, 2010).

[3] Based on data provided in the 2019 United States Renal Dialysis System Annual Report.

rate. Thus, quality is the primary strategic variable that dialysis providers can compete on. Third, concerns about the quality of patient care and the lack of quality transparency have long existed in the dialysis sector, thus prompting the introduction of quality disclosure mandate as a part of the Medicare Improvements for Patients and Providers Act of 2008. The act requires that CMS evaluates and ensures public disclosure of information about quality for all certified dialysis facilities in the US.

We use the introduction of the 2008 Act to study how an increase in quality transparency in the dialysis sector affects competitors' market entry and location decisions and, subsequently, how new competition affects patient outcomes. Using a difference-in-differences design, we document that disclosure of quality information stimulates new entry by rivals in geographic areas with low quality incumbent facilities. For example, an incumbent facility in the bottom 5^{th} quality percentile faces a 27% higher likelihood of a competitor opening a nearby facility after the introduction of the transparency regulation. We also show that, conditional on entry to a local market, new entrants locate closer to incumbents with lower quality. We estimate that transparency-driven entry affects approximately 5% of incumbent facilities, caring for roughly 24,000 patients annually (at an estimated cost of $2 billion).

A useful feature of our setting is that the disclosed quality score relies on data lagged by two years, which makes it effectively impossible to "manage" quality in anticipation of the regulation. Nevertheless, we employ several sets of tests to rule out concerns that our results are confounded by unobservables. We show that the effect of transparency regulation occurs immediately around the year of its introduction and does not exhibit pre-trends. We also conduct a placebo analysis that uses different event years and shows either an insignificant or weaker effect compared to the results from our main analysis. Furthermore, our inferences are unaffected when using a two-stage estimation that controls for the known determinants of quality in the first stage and relies on the unexplained quality in the second stage.

In addition to our baseline difference-in-differences design, we exploit two alternative identification strategies. First, we exploit the staggered addition and removal by CMS of sub-components of the quality score (e.g., addition of measure of vascular access quality in 2014) as a source of exogenous variation in a facility's *disclosed* quality. Note that adding or removing sub-components of quality affects each facility's score differently. This design allows isolating facility-level variation in the quality score driven purely by changes in the reporting requirements and not economic fundamentals. Yet, such variation should be relevant for competitors' decisions. Indeed, we continue to find that disclosure of inferior incumbents' quality prompts new market entry by competitors.

Second, we construct an instrument by leveraging variation in physicians' preferences regarding the initiation of the dialysis treatment depending on the level of kidney function.

Some physicians recommend starting dialysis treatments relatively "early", while others view it as the last resort for patient treatment (Scialla et al., 2014). Consequently, facilities exhibit variation in quality indicators, such as hemoglobin levels, stemming from physicians' ex ante preferences. This physician-driven variation is plausibly exogenous as it is beyond a facility's control and is causally unrelated to (other) economic determinants of entry decisions.[4] The instrumental variable estimation indicates that our main findings continue to hold.

We also study heterogeneity in entry incentives as a function of barriers to entry created by Certificate of Need (CON) Laws. CON laws exist in eleven states, and were initially intended to incentivize the geographic expansion of medical providers by creating barriers to entry into markets with existing facilities. These laws require that new entrants receive costly approval by establishing the presence of local need. Transparency regulation is unlikely to be effective at stimulating entry in the presence of CON laws. Indeed, we find no effect of the transparency regulation in CON states. In non-CON states, however, transparency regulation increases the probability of a new facility opening nearby a low-quality incumbent.[5]

We next examine the mechanism driving new entry around low quality facilities. Conceptually, enhanced quality transparency should increase the elasticity of demand with respect to quality. Thus, we expect that the matching of patients to facilities becomes more sensitive to the quality of these facilities. To test this conjecture, we examine new patients' flows to specific facilities. We observe a reduction in new patient referrals to the lower-quality incumbents when a new facility opens nearby, following the introduction of new disclosure requirements. Moving from the 95^{th} to 5^{th} percentile of quality reduces new patient referrals to a facility, on average, by 32% under the new regime. This loss of new patients translates to $147 thousand in lost revenues (or 4.4% of annual patient revenues) for the incumbent, on average, in the first year alone. Moreover, the effect of transparency on referral networks is widespread, as we find that moving from the 95^{th} to the 5^{th} percentile in quality decreases the number of referring physicians to a facility by three (i.e., by 60% of the mean number of referring physicians to a facility).

Having established the effect of transparency on competition among healthcare providers,

[4]Specifically, physicians refer patients to start dialysis based on a test of how well the kidneys remove toxins from the blood—referred to as the Glomerular Filtration Rate (GFR). GFR has an increasing and monotonic mapping to how well kidney-cleaned red blood cells hemoglobin to carry oxygen to the body. Hemoglobin levels either too high or too low are indicative of poor kidney function, and are a primary measure of quality under the Act of 2008. Thus, patient GFRs at initiation that are either too high or too low result in worse facility quality driven by these doctors' preferences for early or late admission.

[5]These results further alleviate concerns that our main result is due to unobservables correlated with quality, as such interpretation would need to explain why the results do not persist in states that feature barriers to entry.

we study how such effects impact consumers. Prior studies argue that improved competition is expected to have a positive effect on patient health outcomes (e.g., Eliason et al., 2020; Wollmann, 2021). In the absence of competition, providers have incentives to reduce patient-care costs, which leads to less favorable clinical outcomes. In theory, however, competition need not lead to improved quality when markets are heavily regulated (e.g., Katz, 2013; Moscelli et al., 2021). We investigate the effect of competition on patient care quality at incumbent facilities by examining (1) changes in patient health outcomes, and (2) changes in labor inputs to patient care.

Using the complete treatment histories of the US population of dialysis patients, which exceed 4 million observations, we test whether the increased competition following the introduction of the quality transparency program had an effect on the likelihood of incumbent patient hospitalization. Dialysis patients are, on average, hospitalized twice per year for about 11.2 total days. Consequently, about 40% of total Medicare expenditures on ESRD patients are spent on hospitalizations. Using a within-patient difference-in-differences design, we show that patients receiving care at incumbent facilities experience a decline in hospitalization rates when a higher quality competitor enters the market under the new transparency regime. In terms of the economic magnitudes, reduced hospitalizations alone saves Medicare approximately $51.6 million annually.[6]

One plausible mechanism driving this improvement in patient outcomes is that incumbent facilities increase their investments in patient care and services. Indeed, we find evidence that, following an increase in competition, incumbent facilities provide patients with enhanced access to nurses and social workers who support patients' medical and emotional needs. Collectively, we conclude that the increase in quality transparency benefits patients by improving healthcare quality.

Our study contributes to the literature on the industrial organization of the healthcare sector (e.g., Eliason et al., 2020; Wollmann, 2021; Curto et al., 2021; Einav et al., 2018; Grieco and McDevitt, 2017). To the best of our knowledge, ours is the first study that documents a link between quality transparency and competition over healthcare quality, as evidenced by (i) market entry decisions and (ii) an increased elasticity of demand with respect to quality. We also contribute to the literature on the determinants of healthcare quality. While the quality of healthcare depends on factors such as price, regulation, and market power (Grieco and McDevitt, 2017; Eliason, 2019; Eliason et al., 2020), our analysis suggests that enhanced transparency also leads to increased healthcare quality. Finally,

[6]We also consider whether facilities selectively admit patients that may improve their scores, and we find no evidence that facilities alter the mix of patients they admit following the transparency mandate. This issue is also addressed by our design that is based on within patient variation. See section 5.3 for additional details.

our study adds to the literature linking information transparency and economic behavior (see Dranove and Jin, 2010, for review).[7] While this literature focuses on the disciplinary effect of disclosure requirements on the disclosing party, we establish the effect of quality disclosure on rivals' actions. We show that competition is an important channel through which transparency leads to improved consumer outcomes, answering calls for research on *how* transparency can improve product or service quality (Dranove and Jin, 2010; Leuz and Wysocki, 2016).[8]

Our findings are also relevant for policy discussions related to the effects of transparency initiatives in the healthcare sector. The results from our study suggest that, in addition to requiring a minimum level of quality or imposing fines and penalties for poor quality, disclosure requirements can be an effective tool to increase competition and incentivize quality improvements. However, transparency regulation is ineffective in the presence of entry barriers. Our study highlights one such barrier created by CON Laws, which have been increasingly subject to criticism (Mitchell et al., 2017). Our results suggest that, at a minimum, regulators should consider quality of incumbent facilities when assessing local "need."

The remainder of this paper proceeds as follows. Section 2 discusses institutional features of the kidney dialysis sector and related academic literature. Section 3 describes our sample and key variables. Section 4 describes our research design and presents results on the effects of transparency on healthcare competition. Section 5 presents results on changes in patient outcomes following increased transparency. Section 6 provides concluding remarks.

2 Background and Empirical Predictions

2.1 Kidney Dialysis Market

One in seven adults in the US have poorly functioning kidneys (U.S. Renal Data System, 2020).[9] Either a hemodialysis procedure or a kidney transplant is required for the survival of individuals with advanced kidney disease. Given that transplants are rarely available (e.g.,

[7] For example, Jin and Leslie (2003) show that disclosure of restaurant hygiene reduces the likelihood of food-borne illness, Kolstad (2013) shows that disclosure of surgeon quality increases the quality of surgical services, Johnson (2020) shows that publicizing violations of workplace safety reduces on the job injuries, and Eyring (2020) shows that physicians respond to disclosure of subjective patient ratings.

[8] Several studies in corporate financial reporting examine the link between transparency and competition, and show that increased transparency about financial results increases competition (e.g., Granja, 2018; Breuer, 2021).

[9] The kidneys perform several vital functions. When functioning properly, kidneys filter waste and excess fluid from the body and secrete essential hormones; and when not functioning properly, harmful toxins accumulate, which can lead to complications, including heart disease, bone disease, and central nervous system damage.

Akbarpour et al., 2020; Agarwal et al., 2021), nearly half a million people in the US—the vast majority of kidney disease patients—receive some form of dialysis treatment, with the most common form being hemodialysis (U.S. Renal Data System, 2020).[10]

Hemodialysis uses a medical device that filters out toxins from the blood that poorly functioning kidneys are unable to do. Most hemodialysis procedures are conducted on an outpatient basis at dialysis facilities (typically three times per week for four hours at a time). As of 2017, over 7,000 privately-run outpatient dialysis facilities in the US treat approximately 460,000 hemodialysis patients on a regular basis.[11] Most of these facilities are operated by for-profit companies. DaVita and Fresenius are the two largest operators, with a combined market share of over 60%. Appendix A shows the distribution of all dialysis facilities across states in the US.

Since 1973, nearly all patients receiving dialysis treatment in the US are entitled to health insurance coverage from Medicare. As a result, Medicare is the single largest payer of dialysis-related healthcare claims, accounting for approximately 80% of all treatment reimbursements. This amounts to approximately 7% of total annual Medicare expenditures (U.S. Renal Data System, 2019).[12]

Because of the prevalence of Medicare coverage, which fixes the reimbursement rate per dialysis treatment, doctors and patients primarily consider factors other than price when choosing a dialysis facility. Location, i.e., the proximity of a facility to the patient, is one of the most important considerations when choosing a dialysis facility for treatment (Stephens et al., 2013; Eliason, 2019; Wollmann, 2021). The average patient residing in an urban area travels 6.2 miles from their home to a dialysis facility, with the next nearest facility being 10.6 miles away from their home on average (Stephens et al., 2013).[13]

A facility's clinical quality is another key factor relevant to doctors' and patients' decisions. However, quality is largely unobservable to doctors and patients. Over the past two decades, US regulators have been increasingly concerned with informing doctors and patients about the quality of dialysis facilities. In 2001, Medicare launched an initiative to improve the information about quality by creating an online portal—the Dialysis Facility Compare (DFC) website—that published raw data on three measures of quality related to the degree of adequacy of the dialysis treatment procedures in filtering blood, anemia control, and

[10] Annually, the ratio of dialysis patients to recipients of kidney transplants is approximately 25 to 1 (U.S. Renal Data System, 2020).

[11] Hereafter, for brevity, we use the term "dialysis" to refer to "hemodialysis."

[12] Private insurers, who typically reimburse facilities at higher rates compared to the regulated Medicare rates, are the second largest payer in the dialysis market. Private insurance covers up to 30 months of dialysis treatments, starting at initiation.

[13] Using the distance between the zip codes of patients' residences and the central points of the zip codes of the facilities visited, Wollmann (2021) documents similar patient travel patterns.

patient survival rates.

The DFC initiative was deemed largely unsuccessful, as few people used the website, and those who did found the information to be difficult to understand since it was presented in technical and statistical terms (Trisolini et al., 2006). Furthermore, the measures of quality were uninformative as they did not sufficiently differentiate the facilities from one another.[14] These deficiencies prompted a more significant change in dialysis quality transparency, namely, the Medicare Improvements for Patients and Providers Act of 2008, which we discuss next.

2.2 New Quality Transparency Regulation

The Medicare Improvements for Patients and Providers Act of 2008 introduced the End-Stage Renal Disease Quality Incentive Program (ESRD QIP) with the objective to promote "high quality services in renal dialysis facilities." In January 2011, the Centers for Medicare and Medicaid announced that the program's effective start date was January 1, 2012. The new law introduced several significant changes:[15]

First, on January 1, 2012, regulators started measuring a "Total Performance Score" for each facility. The initial scoring methodology weighted the importance of underlying data about the three clinical quality indicators: urea reduction, anemia control (e.g., low hemoglobin count), and high hemoglobin count.[16] Importantly, the total performance score is constructed based on lagged data. For example, data collected from claims in 2010 are used to calculate the first performance score published in January 2012. Because this rule was not finalized until late 2010, most claims data for the first performance score had already been submitted to Medicare before facility operators became aware of the measurement methodology.

[14] In 2008, Medicare introduced two new measures for anemia control and updated the way it reported survival rates, since nearly all—i.e., 94%—facilities were performing "as expected." Nevertheless, internet archives of the DFC website indicate that the vast majority of the presentation format and information provided on the website did not change substantially after these adjustments. Furthermore, regulators later updated these measures again—admitting the data was uninformative to consumers seeking to compare facilities—when it was discovered that more than 99% of all patients achieved the prescribed thresholds for anemia control. See the related press release here: https://www.cms.gov/newsroom/fact-sheets/dialysis-facility-compare-dfc-star-ratings-and-data-release.

[15] The MIPPA also mandated the bundling of payments for dialysis services reimbursements, starting in 2011 (i.e., reimbursing dialysis providers with a single comprehensive reimbursement payment to cover a particular healthcare service). Eliason et al. (2022) find that this bundling of payments leads dialysis facilities to reduce their use of injectable anemia drugs for patients, and also discuss and show that the effects of bundled payment on dialysis care are unrelated to the contemporaneous introduction of the ESRD QIP.

[16] Appendix B provides a summary with further detail about the components of the Total Performance Score methodology.

Second, following the calculation of the Total Performance Score for each facility, CMS publicly discloses the score on the CMS website. Furthermore, facilities must prominently display the quality certificate stating the facility's score and how it compares to the national average (see Online Appendix Figure 1 for an example).

In addition, the ESRD QIP included a monetary penalty that allows Medicare to withhold from 0.5% up to 2% of reimbursements from a facility depending on the facility's total performance score. In 2012, facilities with a score from 21 to 25 out of 30 would have 0.5% of reimbursements withheld, with further reductions of 0.5% for every five points below that.[17] Based on these thresholds, regulators initially estimated that about 27 percent of facilities would have reimbursements withheld in the first year of the program (DHHS, 2011).

During the two years immediately following the introduction of the program, CMS continued to refine the measurement of clinical quality. For example, in 2014, a measure of vascular access quality was added, and an ability to "earn points" for quality improvements was simultaneously introduced. By 2018, the methodology aggregated eleven indicators of clinical quality for each facility. See Appendix B for additional details about modifications to the measurement methodology over time.

2.3 Empirical Predictions

Because prices for dialysis treatment are largely fixed, the key strategic variables that dialysis facilities compete on are location and treatment quality. However, if the information about quality is poor, physicians are unlikely to refer patients to higher-quality facilities, nor are patients able to consider switching to a better-quality facility. Accordingly, a key rationale for enhancing the transparency of clinical quality is to strengthen providers' incentives to compete on quality. When quality is more transparent to doctors and patients, we expect the elasticity of demand with respect to quality to increase, i.e., demand becomes more sensitive to quality changes, and this in turn creates pressure to improve quality (Dranove and Satterthwaite, 1992; Dranove et al., 2003b; Katz, 2013).

To study the effect of quality transparency on competition, we examine whether dialysis providers' decision to enter a particular local market varies based on the quality of information about incumbent facilities.[18] We predict that an increase in information about

[17] In 2014, the first time scores were presented out of 100, the minimum score before payment reductions was 53 out of 100; in 2015, this was adjusted to 60 out of 100; in 2016, it decreased to 54 out of 100; in 2017, it increased to 60; and in 2018, it was decreased to 49 out of 100.

[18] The number of dialysis facilities in the US has grown from 5,295 in 2012 to over 7,400 in 2018 (see Appendix A). Over the same period of time, the number of patients receiving in-center dialysis treatment has expanded from 400,000 to over 460,000 (U.S. Renal Data System, 2020), suggesting that the growth in facilities is driven by an increasing need for dialysis services.

the quality of care resulting from ESRD QIP transparency program increases the propensity of competitors to open new facilities nearby low-quality incumbents. We also examine whether, conditional on entry, the entrant's decision of where to locate a facility is influenced by quality transparency. We expect new entrants to locate their facilities closer to low-quality incumbents following the implementation of transparency regulation.[19]

We also study the mechanism driving market entry and location decisions. Patients' lack of willingness to travel long distances for dialysis treatment renders the demand for dialysis to be inelastic with respect to quality. The elasticity is expected to increase, however, when a new nearby facility opens up, but only if information about quality is available. A prominent way higher-quality entrants can benefit from this increase is by capturing patient referrals. Such a strategy is more likely to succeed following the transparency program initiation, when patients and referring physicians observe the quality score for local facilities.

Finally, we examine whether quality transparency, via its effect on competition, causes improvements in the quality of healthcare. We predict that an increase in competition provides incentives to incumbent facilities to improve the quality of service. Consequently, the opening of a nearby higher-quality facility, following the new transparency regulation, is expected to improve the incumbent's incentives and benefit their patients via lower risk of hospitalization and higher investments into quality.

3 Data and Descriptive Statistics

3.1 Data Sources

The data used in this study comes from four primary sources. First, we obtain facility-level data from the Centers for Medicare & Medicaid Services (CMS) website. We use ESRD QIP annual files and archived DFC quarterly files to obtain the total performance score, its components, address, unique identifier, certification date, and corporate owner for 8,205 certified US dialysis facilities. We normalize the total performance score to vary between zero and 100. Staffing levels, including the number of nurses, clinical staff, and social workers, are from the Renal Facility Cost Reports. The sample consists of 38,522 facility-year observations, which amounts to 85% of the full population, for the period 2008-2015.[20] We drop observations when the total performance score or other variables of interest

[19] In contrast, if information about the quality of incumbents is not a first-order consideration for rivals' entry decisions—e.g., if quality measures are viewed as easily manipulable and effectively uninformative about actual underlying facility quality—we should not find evidence of competitors locating new facilities nearby low-quality incumbents.

[20] We limit the period of analysis from 2008 to 2015 due to data limitations.

are missing.[21] Online Appendix A provides details on how we construct our facility-level dataset (see also Online Appendix Table 1).

Second, we obtain granular patient-level data that includes complete treatment histories and health outcomes from the United States Renal Dialysis System (USRDS). The USRDS is a publicly funded organization that houses a comprehensive set of clinical data comprised of nearly all ESRD patients in the US. Thus we observe close to the entire population of US patients with kidney disease, which consists of 4,772,547 complete patient-year observations. The richness of our data also allows us to identify, at the patient level, when and at which facility a patient initiates dialysis, which we use to document patient flows at the facility level. Online Appendix B describes these data in more detail and explains how we combine it with our facility-level dataset. The USRDS data are also our source for end-stage kidney disease (ESKD) incident counts, which we use to construct a county-level measure of growth in ESKD.

Third, we use physician-level data on patient referrals to facilities which allows us to measure changes in physician referral behavior around the opening dates of new facilities. The data is from the Physician Shared Patient Patterns annual files, also available from the CMS website. The dataset includes 7,972 referring physicians covering six years. Online Appendix G describes these data and our process for matching physicians to dialysis facilities.

Lastly, we manually collect data on state-level "Certificate of Need" (CON) laws, which require operators of dialysis facilities to apply for state-level regulatory approval in order to open, expand, or close a facility. We exploit the heterogeneity of these laws that are applicable to the dialysis sector across states, as discussed in Section 4.3. We use Rural-Urban Commuting Area Codes (RUCA) provided by the 2010 US Census to construct a measure of rurality. Primary RUCA codes, which range from 1 being the most urban to 10 being the most rural, are defined at the Zip Code level.

Some of our tests rely on measuring facilities' total quality scores before 2012. A useful feature of our setting allows us to overcome this challenge. Because CMS collected raw data on the measures that they started using in the calculation of the total performance score since 2010, we can apply the ESRD QIP weighting methodology to pre-2012 data to construct the quality scores for 2010 and 2011. Because the data is not available for 2008 and 2009, we back-fill the missing values based on facilities' 2010-2012 average scores. Online Appendix A describes our methodology. As an alternative, we estimate pre-period quality score using a limited sample of patient-level data from USRDS, which does not require back-filling. We discuss this methodology in Online Appendix D and show that our inferences are similar.

[21] CMS does not calculate scores for facilities with less than eleven patients above the age of 18 during the reporting year.

3.2 Descriptive Statistics

Table 1, Panel A presents descriptive statistics at the facility level for our full sample of dependent, explanatory, and control variables used throughout the analysis.

Approximately 5% of our sample of facility-year observations, or roughly 1,926 facility-years, are identified as new facilities that open near incumbent facilities. Of those new facility entries, 1,541 occur within 5 miles of an incumbent. The mean quality score of all facilities is 87.3. We also present quality scores at the 95^{th}, 75^{th}, 50^{th}, 25^{th}, and 5^{th} percentiles. About 5% of the sample has quality scores of 62 or below, which is considered to be inadequate by Medicare.[22] Figure 3 summarizes the distribution of estimated performance scores from 2008 through 2011 as well as the variation in actual performance scores from 2012 through 2015. The 2012-2013 scores vary less when compared to the 2014-2015 scores, consistent with the changes to the ESRD QIP program over this period. One way to fix the distribution of quality over time is to measure quality based on annual quality deciles. We follow this approach to supplement our main tests. We perform further analysis to probe whether our results are confounded by the estimation error in pre-2012 quality scores discussed in Online Appendix D (see also Table Table 2.)

Panel B presents descriptive statistics for our patient-level data, which includes 4.77 million patient-year observations for dialysis recipients. Of these patient-years, approximately 780,000 exhibit hospitalizations. This amounts to approximately 16.4% of the population of all kidney dialysis patients in the US during our sample period.

Panel C presents summary statistics for clinical, demographic, and ownership characteristics for sub-samples partitioned by quality (lowest and highest quality quartiles) and time (the pre-2012 and post-2012 periods). We do not find significant differences in the clinical characteristics (e.g., hemoglobin levels) when patients are initially admitted to low- vs. high-quality facilities. Low and high quality facilities are also similar in their patient demographics, namely, gender, age, and treatment duration (months with ESRD). Black patients represent a higher proportion of patients at low quality facilities relative to high quality facilities (37.25% vs. 29.18%), however. In terms of facility ownership, we find that the two largest firms, DaVita and Fresenius, own nearly half (48.7%) of all low-quality incumbents and 58.4% of all high-quality incumbents. Further, DaVita and Fresenius have increased their market share from 53.5% (pre-2012) to about 60% (post-2012). The increase occurs via both acquisitions (e.g., Eliason et al., 2020) and new openings. Figure 4 illustrates the distribution of new facility openings by year and ownership. The number of new openings varies, from less than 100 in 2010 to approximately 500 in 2015. Although DaVita typically

[22] At or below this threshold, Medicare imposes economic penalties on providers.

opens the highest number of facilities in a given year, we also find that new openings by independents and other chains represent a third to nearly a half of all openings per year.

4 Quality Transparency and Location of New Facilities

In this section, we examine how the transparency of dialysis providers' clinical quality affects rival firms' entry and location decisions. We start by estimating the effect of incumbent quality disclosure on the likelihood that a competing facility opens nearby. Using a generalized difference-in-differences design, we analyze how new entry and location decisions vary with the incumbents' quality around the introduction of the new regulation. We also conduct a number of additional tests to support the causal nature of our inferences, including a triple differences design (CON vs. non-CON states), the use the staggered changes in the subcomponents of quality scores, and an instrumental variable estimation. Finally, we examine whether patient-referral networks play a key role in attracting rivals to open facilities nearby low-quality incumbents.

4.1 Effects of Transparency on Competition

To examine dialysis providers' decisions to enter new markets, we use the empirical strategy outlined in Figure 1. It relies on the following the difference-in-differences model:

$$\begin{aligned} NewNearestCompetitor_{i,t+2} = \alpha + \beta_1 Post_t \times Q_{i,t} + \beta_2 Post_t + \beta_3 Q_{i,t} \\ + \theta X_{i,t} + \tau_t + \gamma_s + v_i + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $NewNearestCompetitor_{i,t+2}$ is an indicator variable that equals one if in year $t+2$ a competitor opens a new facility that is the nearest facility next to an incumbent facility i, and zero otherwise, $Q_{i,t}$ is an incumbent facility i's total performance score (standardized to be out of 100), and $Post_t$ is an indicator that takes value of one in 2012 and onward (i.e., in the disclosure regime), and zero otherwise. Year t represents the year when the quality score is disclosed. We focus on entry decisions in year $t+2$ because it takes roughly 1.5 years from planning to completion (including regulatory approval) to open a new facility.[23] Our main coefficient of interest, β_1, captures the average marginal effect caused by an increase in transparency on entry decisions by rival firms. In all of our specifications, $X_{i,t}$ represents a

[23]This estimated amount of time to open a new facility includes the time it takes for the provider to be approved and certified but also the time it would take to find a location suitable for a dialysis facility and negotiate the lease, in addition to the time it would take to develop the business plan for the new facility. As an example, for performance scores viewed by rivals in 2012, the earliest a new rival facility could open would be in 2014, which is consistent with projected timelines we find in new facility applications.

vector of other predictors of new facility locations, including the county-level growth rate in ESKD, the Medicare payment reduction percentage, and a measure of the degree to which the incumbent facility is located in a rural versus urban geographical area. Equation (1) also includes year (τ_t) fixed effects and state (γ_s) or facility (υ_i) fixed effects. We estimate equation (1) using a linear probability model. In all specifications, we cluster standard errors, two ways, at the year and at the firm levels.

Table 2, Panel A presents the results. Column (1) indicates that, after the transparency mandate was introduced, competitors are significantly more likely to open new facilities nearby lower quality incumbent facilities, as follows from the negative and statistically significant coefficient on the interaction $Post \times Quality$. In column (2), we also include facility fixed effects to estimate the within-facility effect of the transparency program on the likelihood of new entry near a low-quality incumbent facility. The results are similar to those in column (1), both statistically and economically. Columns (3) and (4) repeat the analysis in columns (1) and (2), respectively, restricting new entrants only to the facilities opening within 5 miles of the incumbent. This choice is motivated by our conversations with nephrologists and the evidence that distance is a key factor in the patients' facility choice. The evidence in both columns—i.e., with and without facility fixed effects—continues to indicate a similar positive effect of the transparency program on the likelihood of entry by rival providers in markets with low-quality incumbent facilities. [24]

Finally, while the analysis in columns (1) through (4) in Table 2, Panel A is based on the continuous treatment variable, columns (5) and (6) rely on within-year quality decile ranks and are estimated with and without facility fixed effects, respectively. The rank-transformation is intended to ensure that our inferences are not driven by any possible change in the distribution of the total quality score due to modifications to the methodology that took place over our sample period. We continue to find that competitors are more likely to open new dialysis facilities nearby lower quality incumbents after the introduction of the transparency regulation in 2012.[25] Our results also continue to hold when we use an alternative methodology, which, as described in Online Appendix D and presented in Online

[24] In Online Appendix H, we consider an alternative research design that estimates a first-stage model of the determinants of quality based on a vector of local factors to determine a predicted level of quality; uses the residual from this first-stage model to measure unexpected quality; and replaces quality in the second-stage with the residual from the first-stage model. Results presented in Online Appendix Table 5 show that our inferences are unchanged.

[25] Prior literature finds that the lack of competition in dialysis markets is partially driven by its highly concentrated nature, with dialysis provider firms Fresenius and DaVita owning approximately two thirds of all dialysis facilities (U.S. Renal Data System, 2019; Eliason et al., 2020). Consistent with this degree of market concentration, of the 1,130 total new facility openings nearby incumbents during the *Post* period in our sample, 353 (31%) are by DaVita, 382 (34%) are by Fresenius; the remaining 395 (35%) are by regional, locally owned dialysis facility owners.

Appendix Table 2, uses a limited sample of patient-level data to more directly measure the pre-2012 quality scores.

While the results above are similar across alternative specifications and measurement choices, their magnitudes are difficult to interpret. To help assess the economic magnitudes, Table 2, Panel B, presents the probabilities of *rivals* opening a new facility at the 95^{th}, 75^{th}, 25^{th}, and 5^{th} percentiles of *incumbents'* quality. These estimates show that, in the new disclosure regime, a reduction in an incumbent's quality from the 95^{th} to 5^{th} percentile—or from a score of 100 to 62—increases the likelihood of a rival opening a nearby facility by 15.7%. In contrast, the opposite occurs in the non-disclosure regime. In particular, a decline in an incumbent's quality from the 95^{th} to the 5^{th} percentile, prior to 2012, is associated with a 26.4% reduction in the probability of a rival opening a new facility near the incumbent.

Collectively, these results indicate that a drop in quality from the 95^{th} to 5^{th} percentiles results in a greater than 40% increase in the probability of new entry by rivals—moving from a -26.4% to 15.7%—following the increase in quality transparency. Moreover, if we consider only the incumbent facilities with quality scores of 62 or lower (i.e., the 5^{th} percentile in our sample), the probability of a new facility opening nearby increases by 27%—from 7.8% to about 10%—in the post-2012 period. We observe similar—although less pronounced—patterns when we examine the shift from the 75^{th} to 25^{th} percentiles in quality. Overall, these results suggest that the transparency regulation had an economically significant effect on the entry of new competitors.

4.1.1 Parallel trends

A key threat to a causal interpretation of our results in Table 2 is that our treatment variable is correlated with other (omitted) variables, which in turn may influence the probability of new entry.[26] Indeed, the aforementioned positive association between the probability of new entry and quality in the pre-period is suggestive of this possibility (e.g., see Panel B). To alleviate this concern, we perform a diagnostic test to help assess the validity of the parallel trends assumption. We re-estimate equation (1) with separate year indicators (instead of a single *Post* dummy) and allow for their interactions with the treatment variable. We set 2011 as a benchmark year and plot coefficient estimates over time. Figure 5 presents results. The vertical axis measures the treatment effect—i.e., the coefficients on the $Year \times Quality$ interaction. We find no evidence of a pre-trend, which is inconsistent with the presence of confounding factors driving our results.

[26]For instance, if observable features of a facility's operations and performance—e.g., patient congestion, transplant and death rates—are correlated with quality, we would expect to find a relation between quality scores and entry in the pre-period.

Further, we observe evidence of a significant treatment effect that begins in 2012 and persists over time. Notably, the 2013 estimate appears considerably larger in economic magnitude relative to 2014-2015 (and 2012) estimates. One possible explanation for this is that, in 2013, CMS dropped one clinical measure from the calculation of total performance scores. This explanation seems unlikely as the result continues to hold after we properly rescale the measures or use yearly quality decile rankings. A more plausible explanation is that facilities started to invest in quality in response to new entry (or threat of entry).[27] We provide further evidence on incumbents' quality response in Section 5.

4.1.2 Placebo Analysis: Alternative Post-Treatment Years

While the trends analyses provide visual support for our empirical analysis, we also conduct a placebo test. Specifically, we examine how our main coefficient estimates change when we change the actual intervention year of the transparency program to a placebo intervention year. To do so, we re-estimate equation (1) when using either 2009, 2010, 2011, 2013, 2014, or 2015 year to construct the *Post* indicator.[28]

The results from estimating these placebo tests are summarized in Online Appendix Table 4. This table shows insignificant but increasing coefficients on the $Post \times Quality$ interaction when the placebo event year varies between 2009 through 2011. However, this coefficient monotonically declines in absolute value relative to 2012 when the placebo year varies between 2013 and 2015. The table shows that the maximum economic magnitude of the effect is achieved in 2012, which is the actual year when the program was implemented. Collectively, these results further reinforce the interpretation of our results suggesting that an increase in quality transparency, *per se*, is driving the documented increase in new entry into local markets.

4.2 Distance to Local Competitors

A complementary approach to examining the effect of quality transparency on competition in dialysis markets is to study rivals' decisions regarding how far away to locate from an incumbent, conditional on entering into a new local dialysis market. We analyze how the geographic distance between new facilities and their closest rivals varies with the introduction of the transparency regulation.

[27] Recall that at the time of adoption, the first disclosed quality scores were lagged by two years which effectively precluded companies from responding to regulation by changing quality.

[28] The results from these tests also help rule out that our results are not driven by other changes or trends in the dialysis sector over our sample period.

Figure 2 presents non-parametric probability distributions for the pre- and post-2012 periods of the distances to the nearest rival dialysis facility. We find that the entire distribution shifts to the left in the post-2012 period, i.e., when firms have more information about quality, they are more likely to locate closer to a rival.

We test the link between quality transparency and the distance between a new entrant and incumbent facility more formally by estimating the following difference-in-differences model:

$$\begin{aligned} Distance_{i,t+2} = \alpha + \beta_1 Post_t \times Q_{i,t} + \beta_2 Post_t + \beta_3 Q_{i,t} \\ + \theta X_{i,t} + \tau_t + \gamma_s + \upsilon_i + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $Distance_{i,t+2}$ is the natural logarithm of the geographic distance (in miles) to an incumbent facility in year $t+2$ within a local market (the local market is defined as any incumbent facility within 10 miles of a newly-opened facility, which facilitates our focus on direct competitors); $Post_t$ is an indicator variable that takes value of one for years 2012 and beyond, and zero otherwise; and $Q_{i,t}$ is an incumbent facility i's total performance score. The main coefficient of interest, β_1, captures the change caused by the introduction of the transparency program in the effect of incumbents' quality on new entry by rivals. In all our specifications, $X_{i,t}$ represents a vector of other predictors of new facility locations, including the county-level growth rate in ESKD, the Medicare payment reduction percentage, and a measure of rurality. Equation (2) also includes year (τ_t) and state (γ_s) or county (υ_i) fixed effects. We cluster standard errors two ways at the year and at firm levels.

The results from estimating equation (2) are presented in Table 3. Columns (1) and (2) report results from specifications without and with facility fixed effects, respectively. Across both specifications, we find that the coefficient on the interaction $Post_t \times Q_{i,t}$ is positive and statistically significant. This implies that following the introduction of quality transparency regulation, new entrants choose to locate at shorter distances to low quality incumbent facilities. Columns (3) and (4) repeat this analysis from columns (1) and (2), respectively, using within-year quality decile ranks of facility i's total performance score. We continue to observe similar effects of transparency on the choice of distance to incumbent facilities.

4.3 Exit Decisions

In addition to facilitating market entry, transparency about quality should also encourage the exit of lower-quality providers. While we do not directly observe exit decisions, in most cases the exit occurs via acquisitions. To examine whether the transparency regulation impacts acquisitions of low-quality facilities, we replace $NewNearestCompetitor$

with *ChangeOwnership*—an indicator for whether the facility is acquired—and re-estimate (1). The results are presented in Online Appendix Table 3. Consistent with quality transparency facilitating the exit of low-quality incumbents, we find that following the introduction of transparency regulation, the likelihood of low-quality incumbents being acquired increases. Relative to new openings, however, we find that acquisitions occur less frequently—approximately one-third relative to the rate of new openings—after the transparency regulation is implemented.

4.4 Barriers to entry

Despite the evidence of parallel pre-trends and the robustness of our results to controlling for observable determinants of quality in a first stage, the confounding effect of unobservables cannot be fully ruled out. To further support a causal interpretation of our results, we exploit across-state variation in barriers to entry. This analysis can be interpreted as triple difference-in-differences; it helps further rule out possible confounding trends in our estimates.

While in most US states dialysis providers face few regulatory barriers, this differs in eleven states, where entry into the dialysis-services market is regulated through (dialysis-specific) "Certificate of Need Laws" or CON laws (see Appendix A for the list of CON law states). CON Laws were introduced more than four decades ago by the National Health Planning and Resources Development Act of 1974. The goal of the Act was to incentivize geographical expansion and avoid duplication of capacity in areas where services are already available. It provided strong incentives for states to adopt CON laws that require that healthcare providers prove to the regulators the existence of local need for their services. CON laws created significant barriers to entry (Mitchell et al., 2017; Stratmann and Russ, 2014; Baker and Stratmann, 2021) and have consistently been subject to calls for abandonment.[29] In the 1980s, Congress repealed the Act and subsequently many but not all states have removed their CON requirements.

Dialysis providers in CON law states must apply for approval from the state planners before opening, relocating, or expanding dialysis facilities. The approval hinges upon whether the proposed new facility will help to meet a current or expected local need for dialysis, based upon factors that include the presence of existing dialysis centers in the area, current rates of capacity utilization, population, and population growth.[30] The quality of incumbent facilities is not considered during this approval process.

[29]https://www.usnews.com/news/best-states/articles/2021-07-09/on-the-heels-of-the-pandemic-states-should-get-rid-of-certificate-of-need-laws.

[30]See the following for an example of a CON application: www2.illinois.gov/sites/hfsrb/Projects/ProjectDocuments/2020/20-035/20-035%20Sauganash%20Dialysis%20CON%20Application.pdfsearch=20%2D035.

These requirements deter competition by imposing substantial costs on entrants wishing to open new facilities near low-quality incumbents. In the states without dialysis-specific CON laws, providers are only required to obtain a license, which is a less complex process with faster turnaround times. For example, in Ohio, a non-CON state, the facility licensing process requires only a three-page application whereas the applications in states with CON laws tend to be much longer and more detailed (hundreds of pages in some cases), and involve considerable litigation and lobbying efforts.[31]

We examine whether the effect of quality transparency on facility openings differs in non-CON vs. CON states. To do so, we partition our sample into sub-samples based on the presence of CON laws in a given state. Subsequently, we estimate equation (1) for each sub-sample and compare the coefficient estimates across samples.

The results from this analysis are presented in Table 4. Columns (1) and (2) are based on estimating equation (1) for non-CON and CON law states, respectively. We find that the coefficient on the interaction $Post \times Quality$ remains negative and statistically significant in the non-CON laws sub-sample, suggesting that increased transparency about quality enhances competition from rivals. The economic magnitude of the coefficient is in fact higher as compared to that based on the overall sample used in Table 2. In contrast, for the sample of facilities exposed to CON laws, we find no statistically significant coefficient on the $Post \times Quality$ interaction. Further, we find that the difference between the two coefficients of interest across columns (1) and (2) is statistically significant based on a Wald test.

We also examine parallel trends by estimating equation (1) using separate year indicators and plotting the coefficients. Figure 6 shows no evidence of pre-trends in either CON or non-CON law states. However, after the introduction of enhanced quality transparency in 2012, we observe a distinct change in the behavior of competitors in non-CON law states where the probability of opening new facilities near low-quality incumbents noticeably increases. In contrast, we see no such change in behavior in CON law states following 2012.

Overall, these tests help us to further rule out a possible concern that our results in Table 2 reflect differential trends in the demand for dialysis among patients at lower vs. higher quality incumbent facilities.

[31] Regardless of the (proposed) facility's location, however, all new dialysis facilities in the US must also be certified by Medicare to be reimbursed for services provided to Medicare-covered patients, as nearly 80% of patient claims for dialysis treatment are reimbursed by Medicare. Consistent with the comparatively larger costs imposed on new entrants by CON laws, using certification dates disclosed by Medicare compared to CON approval dates for the same facilities, we find a roughly nine-month difference between CON approval and Medicare certification.

4.5 Alternative Identification Strategies

In addition to our baseline difference-in-difference design, we exploit two alternative identification strategies to further address concerns that observable (omitted) variables may be driving our results. The first strategy relies on the staggered addition and removal of subcomponents of the quality score as a source of exogenous variation in the metric relevant for rivals. The second strategy relies on an instrument that is plausibly outside of a facility's control but is correlated with quality. We describe these tests in what follows.

4.5.1 Variation in Quality Measures over Time

During our sample period, CMS re-evaluated the inclusion of quality score sub-components on an annual basis. As a result, several sub-components that jointly make up the total quality score were added or removed in a staggered manner. When the change in methodology is announced, CMS requires the use of data lagged by two years to prevent manipulations of the measure in anticipation of the change(s). Thus, in the year when a quality indicator is added to or removed from the calculation of the quality metric, an exogenous change to the total quality score occurs at the facility level while there is no real change in the facilities' economic characteristics. Because rivals care primarily about the incumbents' *reported* quality score (as opposed to its components), the changes in measurement methodology induce exogenous variation that allows us to identify the effect of disclosed quality information on entry decisions.

To implement these tests, we construct a variable *QualitySubscoreAddDrop* that captures the effect on a facility's quality score of the addition or removal of quality score sub-components in any given year. The variable takes the value of $+1$ if a change in the measurement benefits a given facility in terms of improving its reported quality score, -1 if the change results in a lower quality score, and 0 if it has a neutral effect. We discuss the construction of this variable in more detail and provide additional information about the changes in the composition of the total performance score in Online Appendix E.

We use *QualitySubscoreAddDrop* in an ordered logit regression to explain new entry decisions. This analysis is reported in Table 5. Consistent with our previous findings, we observe that the likelihood of new entry by a competitor increases when incumbents' quality deteriorates. Indeed, column (1) indicates that the coefficient on the variable of interest is the negative and statistically significant. Further, column (2) shows that this effect is robust to the inclusion of facility fixed effects. In sum, in line with our main hypothesis, we find evidence that entry decisions are sensitive to variation in disclosed information on quality.

4.5.2 Instrumental Variable Analysis

Another way to address the issue that quality is a choice variable by a given facility, e.g., it can respond to competitive pressures making it more difficult to detect an effect of transparency on competition, is an instrumental variable estimation. A valid instrument requires a source of variation in the facility's quality score that is unrelated to facility-level decisions or characteristics. We use variation in physicians' preferences—due to their professional beliefs and judgments—over weather to recommend that a patient initiates dialysis treatments depending on the patient's level of glomerular filtration rate (GFR), a key clinical measure of how well a patient's kidneys are functioning (National Kidney Foundation, 2014). Since 1997, guidelines in the US advocate initiating dialysis at lower levels of GFR (e.g., GFR < 10.5), unless other health conditions are present in the patient, in which case early initiation may be advisable. However, there is no consensus among physicians as to what the optimal level of GFR is to initiate the treatment (Scialla et al., 2014). Considerable variation exists in GFR thresholds across physicians and, consequently, across their patients at the time of treatment initiation (Scialla et al., 2014).

Given that a limited set of physicians refer patients to a facility, physicians' preferences induce facility-level variation in GFR numbers. While GFR does not enter the calculation of the quality score, it induces variation in hemoglobin (Hgb), which is one of the primary and consistently required inputs in the quality measurement. Clinical studies show that, at lower levels, GFR is positively correlated with hemoglobin (Hgb) (e.g., Levin et al., 1999; Astor et al., 2002). As a result, physicians who prefer to initiate dialysis either "early" or "late," as defined by prior medical studies (e.g., Cooper et al., 2010), induce variation in the facility's quality score through the relationship between GFR and Hgb. More specifically, early initiation can negatively impact the quality score through the component of score that penalizes a facility for its proportion of patients with high Hgb (i.e., Hgb > 12); late initiation can adversely impact the quality score through the component of score that penalizes a facility for its proportion of patients with low Hgb (i.e., Hgb < 10). We discuss GFR and the mapping of GFR to Hgb levels in more detail in Online Appendix F. The key takeaway of this discussion is that physicians' preferences induce variation in the reported total quality score that is unrelated to the facility's choices while at the same time being relevant to rivals' entry decisions.

We use patient-level GFR information at the time of treatment initiation to construct the facility-level instrument. We then estimate the following first-stage model:

$$Quality_{i,t} = \alpha + \beta_1 BadGFR_{i,t} + \theta X_{i,t} + \tau_t + v_i + \epsilon_{i,t}, \tag{3}$$

where $Quality_{i,t}$ is a continuous variable that equals the total performance score for facility i in year t, and $BadGFR_{i,t}$ is an indicator variable that takes the value of one if patient GFR at initiation is above 11 or less than 7 (corresponding to Hgb levels that are penalized by CMS when calculating the quality scores), and zero otherwise. The use of a binary indicator is motivated by the fact that the quality score is determined by the proportion of patients at a facility with either high or low Hgb, where Hgb is considered high (low) if it is above (below) 12 (10), and is not determined by the *degree* to which Hgb is above or below these thresholds. We describe the patient data used to construct mean GFR in Online Appendix B. In all of our specifications, $X_{i,t}$ represents a vector of facility-level controls variables (described in the notes to Table 6). Equation (3) also includes year (τ_t) and facility (v_i) fixed effects. As previously, in all specifications, we cluster standard errors at both year and firm levels.

Panel A of Table 6 presents results from this analysis. Consistent with our expectations, the results indicate that facility quality decreases with our measure of GFR taken at treatment initiation. The first stage F-statistics range from 10.59 to 19.06. In the second stage, we use the instrumented measure of $Quality$ to estimate Equation (1). We include the same set of facility-level controls and fixed effects as in the corresponding first stage model. The second stage estimates are in Panel B of Table 6.[32] For comparison purposes, column 1 presents our baseline OLS estimates (see Table 2). The estimates in columns (2) through (4) show a negative and statistically significant coefficient on the interaction $Post \times Quality$. This indicates that, following the introduction of the new transparency mandate, competitors are significantly more likely to open new facilities in the vicinity of lower quality incumbents.

Notably, the magnitude of the effect of transparency on competitors' location decisions more than doubles, from -0.00049 in column 1 (our baseline OLS result) to -0.00123 in column (2) after instrumenting for quality. This increased magnitude is consistent with what one would expect if firms are able to "manage" quality, thereby attenuating the effect of quality transparency on competition. Importantly, the positive association between the probability of new entry and quality in the pre-period observed in Table 2 is now negative, in line with what we expect. Collectively, these results provide further support to a causal interpretation of the effect of quality transparency on healthcare competition.

[32]The exclusion restriction for this instrumental variables analysis is that GFR numbers do not affect rival dialysis providers' decisions of where to locate new facilities, other than through the effect of GFR numbers on incumbent facility's own quality. Given that rivals do not know doctors' *ex ante* GFR recommendation thresholds for dialysis initiation, it is unlikely for this instrument to violate this exclusion restriction.

4.6 Patient Referral Networks

We next examine the mechanism that provides incentives to rival firms to compete with low-quality incumbent facilities: new patient referrals. Patient referrals are vital to the economic growth and sustainability of dialysis providers, and are particularly important to new facilities.[33] The granularity of our data allows us to identify new patients who join a facility each year (see Online Appendix B for details). Physicians generally prefer to refer new patients to higher-quality facilities, and having better information about competing providers' quality enables them to do so.

To test this, we estimate the following difference-in-difference-in-differences model to study the relationship between new facility openings and changes in annual incumbents' referrals:

$$\begin{aligned} NewPatients_{i,t} = \alpha &+ \beta_1 Post_t \times NewNearest_{i,t} \times Q_{i,t} + \beta_2 NewNearest_{i,t} \times Q_{i,t} \\ &+ \beta_3 Post_t \times NewNearest_{i,t} + \beta_4 Post_t \times Q_{i,t} \\ &+ \beta_5 Post_t + \beta_6 NewNearest_{i,t} + \beta_7 Q_{i,t} + \theta X_{i,t} + \tau_t + v_i + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $NewPatients_{i,t}$ is a continuous variable that measures the number of new referrals at facility i in year t. $NewNearest_{i,t}$ is an indicator variable that assumes the value of one if the nearest facility to an incumbent is new (and zero otherwise) and $Q_{i,t}$ is a continuous variable that is the quality score of the incumbent. We include a vector of control variables as described in the notes to Table 7. We also include year (τ_t) and facility (v_i) fixed effects, respectively. As in our prior analyses, we cluster standard errors at both the year and firm levels. Given that our patient referral data is measured annually, we exclude from our analysis those new facilities that open after June 30^{th} in a given year, thus allowing sufficient time for referrals to accumulate.

The results from estimating equation (4) are presented in Table 7, Panel A. The coefficient of interest, β_1, measures the effect of new regulation on the extent to which an incumbent's low quality amplifies a loss of new patients when a competitor enters nearby. We find that the patient flows become more sensitive to quality information in response to the new regulation. Column (1) suggests that a decrease of 13 points in the incumbent's quality score reduces the level of new patient referrals to that facility by one patient, on average, after 2012. This effect increases by roughly 33% in column (2) when we restrict our definition of a new entrant to new openings within 5 miles of the incumbent. We also estimate equation (4)

[33] Providers typically attempt to establish networks with referring physicians before opening new facilities. For example, in one recent application to provide dialysis treatments in Illinois, a nephrologist in support of the new facility opening predicted that 63 of her 386 total patients that reside within 5 miles of the proposed facility location would progress to requiring regular dialysis treatment within 24 months of the opening of the new location.

using separate year indicators and plot the coefficients in Figure 3 of the Online Appendix. We find no evidence of pre-trends. In terms of economic magnitudes, moving from the 95^{th} to the 5^{th} percentile of quality after 2012, on average, reduces the number of new patients by four per year per facility, or roughly 32% of the average facility's new referrals. This accounts for an estimated loss of $147,000 per facility in the first year alone (or 4.4% of total annual patient revenue).[34] By the third (fifth) year, this accounts for an estimated loss of 13.3% (22.1%) in total annual patient revenue per facility.[35]

Panel B of Table 7 extends the analysis by changing the dependent variable to be the number of referring physicians who begin referring to new facilities within the first year after the opening of a new facility. This allows us to provide evidence on how widespread the effect of transparency is on the referral network. For this analysis, we use data on physician referral behavior described in Online Appendix G. Collectively, the results in Panel B are similar to those in Panel A. For example, column (2) of Panel B indicates that a change of 13 points in quality score impacts the number of referring physicians by one, on average. Given that the mean number of referring physicians to a facility after 2012 is five, this result suggests that moving from the 95^{th} to the 5^{th} percentile in quality reduces the number of referring physicians to a facility by roughly 60% (i.e., by three physicians). Overall, the results in Panels A and B suggest that, following an increase in quality transparency, the opening of new higher-quality facilities becomes costlier to incumbents both in terms of new patient referrals and a loss of the existing referral network.

While Panels A and B focus on changes in patient and physician behavior in the presence of a new competitor, Panel C examines the effect of quality transparency on patient flows without conditioning on market entry. More specifically, we examine the elasticity of patient flows with respect to quality and how it changed in response to the new regulation. Accordingly, we estimate the model in logs. Our estimates suggest that a 10% decrease in quality reduces new patient referrals by nearly 1.6% in column (1). Notably, we find that the effects of quality transparency on elasticity in patient demand is approximately equal for first-time dialysis patients, in column (2), and the population of patients that switch facilities, in column (3).

[34] Calculations are based on an average reimbursement rate of $235.40 per treatment session for Medicare patients. We assume three treatment sessions per week and 52 weeks per year.

[35] We use total 'Net patient revenues' collected from the Independent Renal Dialysis Cost Report (Form CMS-265-11) to find the average annual revenue per facility and then use this amount to estimate the percent of lost revenue per facility per year.

5 Does Competition Affect Quality?

Our findings in Section 4 consistently indicate that competitors respond to quality transparency by locating new facilities near lower-quality incumbents. New entrants are also able to attract patient referrals from lower-quality incumbents. However, does an increase quality transparency lead to improvements in the quality of care? In this section, we explore whether and how the incumbent facilities respond to entry by rivals. We start by examining the effect on patient health outcomes, and, subsequently, investigate a plausible mechanism behind these changes by focusing on inputs into incumbents' production functions, including changes to levels of employees such as nurses, dietitians, and patient-care staff.

5.1 Patient Outcomes

We use dialysis treatment histories for the population of US dialysis patients to study whether competition induced by the transparency program reduces the likelihood of patient hospitalization. We focus on hospitalizations since they are a key indicator of patient morbidity and overall quality of life. Additionally, hospitalization costs account for approximately 40 percent of total Medicare expenditures for ESRD patients (University of Michigan Kidney Epidemiology and Cost Center, 2016), with dialysis patients on average being hospitalized twice per year.

We examine within-patient changes in health outcomes following the opening of nearby, better-quality competitor facilities by estimating the following model:

$$\begin{aligned} HealthOutcomes_{i,j,t+2} = \alpha &+ \beta_1 Post_t \times NewNearest_{j,t} \times dQuality_{j,t} \\ &+ \beta_2 NewNearest_{j,t} \times dQuality_{j,t} + \beta_3 Post_t \times NewNearest_{j,t} \\ &+ \beta_4 Post_t \times dQuality_{j,t} + \beta_5 Post_t + \beta_6 NewNearest_{j,t} \\ &+ \beta_7 dQuality_{j,t} + \theta X_{j,t} + \tau_t + v_j + \epsilon_{i,j,t}, \end{aligned} \tag{5}$$

where $HealthOutcomes$ is an indicator variable that takes the value of one if patient i at facility j is hospitalized for any cause in year $t+2$. We focus on health outcomes two years after a competitor opens a nearby facility of better quality to allow sufficient time for the disciplinary effects of competition to occur. $NewNearest_{i,t}$ is an indicator variable that equals one if the nearest facility to an incumbent is new, and zero otherwise. $dQuality_{i,t}$ is a measure of quality differential between a newly opened facility and incumbent facilities.[36]

[36]Since the quality of a new local competitor is not publicly revealed until two years after an opening, due to the lagged approach that CMS uses, our measure is constructed using the quality of the incumbent in year t and the quality of the competitor in year $t+2$. The underlying assumption is that incumbents can infer the quality of the new competitor, e.g., if the competitor already has another facility in the local market. We formally test this assumption by using the quality score in year t of another local facility owned by the same

We measure $dQuality_{i,t}$ in two ways: (1) as a binary variable that equals one if the newly opened nearby facility has a higher quality score, and zero otherwise; (2) the difference in quality scores between the new and incumbent facilities. We include a vector of facility-level controls ($X_{j,t}$) as defined in Table 8. In all specifications, we also include year (τ_t) and patient (v_i) fixed effects and cluster standard errors by year and by facility.

Table 8 presents the estimates for equation (5). The estimates in columns (1) through (4) consistently show that the new transparency regulation leads to a decrease in the likelihood of hospitalization for patients at incumbent facilities when a better quality facility opens nearby. Based on column (1), the magnitude of the coefficient suggests that, on average, the probability of a hospitalization decreases by 1.8 percentage points—or a 8.5% decrease relative to the sample mean rate of hospitalization (i.e., 21.2%)—in a given year.[37]

To estimate annual cost savings to Medicare associated with this reduction in hospitalizations, we assume that 40 percent of Medicare spending, or approximately \$12-\$15 billion per year since 2012, is absorbed by hospitalization-related expenses (University of Michigan Kidney Epidemiology and Cost Center, 2016). Approximately 110,000 patients are treated at incumbent facilities that experience entry of new nearby competitors of better quality (or approximately 4.5% of the population of patients in the post period) post-2012. These amounts, along with the 8.5% decrease in the probability of hospitalization, translate in an annual estimated cost savings of \$13.5 billion $\times$ 4.5% $\times$ 8.5% = \$51.6 million to Medicare alone. Collectively, this analysis suggests that quality transparency, via its effect on healthcare competition, improves patients' health outcomes.

5.2 Changes in Incumbent Facility Inputs

We next investigate a plausible mechanism through which improvements in patient outcomes occur by examining the effect of transparency-induced competition on the inputs to dialysis providers' production functions. We use facility-level data on the number of nurses, clinical staff, and social workers employed by the incumbent facilities since this personnel plays an important role in ensuring the quality of care. We follow the methodology in Eliason et al. (2020) by focusing on the changes in the level of inputs from the year before to the year after a new facility's opening. Our model specification is as follows:

firm as the new competitor and find that our results are robust to this alternative approach to measuring the quality of an entrant.

[37] In Online Appendix J, we also consider whether and find some evidence that low-quality facilities respond—in terms of patient care, as measured by hospitalizations—to threat of entry.

$$
\begin{aligned}
\Delta\ Inputs_{i,t+1} = {} & \alpha + \beta_1 Post_t \times NewNearest_{i,t} \times dQuality_{i,t} \\
& + \beta_2 NewNearest_{i,t} \times dQuality_{i,t} + \beta_3 Post_t \times NewNearest_{i,t} \\
& + \beta_4 Post_t \times dQuality_{i,t} + \beta_5 Post_t + \beta_6 NewNearest_{i,t} + \beta_7 dQuality_{i,t} \\
& + \theta X_{i,t} + \tau_t + v_i + \epsilon_{i,t},
\end{aligned} \tag{6}
$$

where the dependent variable, $\Delta Inputs$, is the temporal change in one of several facility-level labor inputs known to influence the quality of dialysis care: nurses, clinical staff, and social workers. All other variables are as previously defined.[38]

Incumbents' response to increased competition is not obvious ex ante. On the one hand, a loss of patient referrals—and a corresponding reduction in revenue—could push incumbents to reduce costs, e.g., to shift from higher-paid registered nurses to less experienced and lower-paid technicians to provide dialysis treatment (e.g., Eliason et al., 2020). Given that it is costly for the patients to switch to another facility, competition may ultimately reduce the quality of service (such a reduction in quality could be optimal in the presence of sufficiently large economies of scale in quality such that firms only invest in high quality if they have enough demand for dialysis services). On the other hand, a loss of referrals to rivals could push incumbents to improve the quality in order to stem losses in revenue. For example, they can increase the time spent on cleaning dialysis stations or the time allocated to patient care and support. Consistent with this latter response, Bloom et al. (2015) document an improvement in management quality as a result of increased competition in U.K. public hospitals.

Table 9 documents incumbents' responses to the opening of a nearby higher-quality facility. We find that the introduction of the quality transparency regulation generally resulted in increased efforts by incumbent facilities to respond to higher-quality entry from the patients' perspective. The incumbent facilities exhibit an increase in patient care as manifested by increases in the number of nurses (column 1) and the number of social workers (column 3), which play critical roles in providing patients with medical and emotional support, respectively. Moreover, we do not find that incumbents switch from using nurses to clinical staff (such as technicians) in order to cut costs.

In Panel A of Online Appendix Table 6, we modify the dependent variable in this analysis to be measured two years after the entry by a competitor and show that investments in patient care following an increase in competition from a higher quality rivals persists. Finally, in Panel B of Online Appendix Table 6, we perform regression analysis that scales the number

[38]For this analysis, we focus on changes in the absolute staffing levels rather than staffing per patient or unit of other service inputs. Focusing on per-patient quantities could result in spurious effects: the denominator can be reduced while the numerator has a lower bound. For example, a dialysis facility with low demand will mechanically have a higher registered nurse-to-patient ratio.

of patient-care staff by the number of dialysis machines at the facility. Although potentially confounded by changes in the number of dialysis stations at a facility, this analysis shows that our results are qualitatively similar.

5.3 Gaming of Quality Scores

We conclude our analysis by addressing a possible concern that facilities can game the quality score in response to the transparency mandate. One way to do this is by altering the mix of patients admitted for dialysis, e.g., only admitting patients with hemoglobin levels that would help the facility obtain a better quality score. Note that several of identification strategies we use (e.g., instrumental variable tests) should not be subject to this concern. Similarly, our results on hospitalizations (Table 8) provide evidence of *within-patient* improvements in patient outcomes and hence are unaffected by possible manipulations of patient mix.

To address this further, we investigate whether facilities appear to selectively admit patients to improve their quality scores by examining the characteristics of newly admitted patients before and after the initiation of transparency regulation. We use a difference-in-differences specification with facility and year fixed effects. Our dependent variables—a set of various patient characteristics at admission—are measured at the facility level and thus capture the average characteristics for patients admitted to the facility before and after 2012. Our measure of quality is an indicator variable that assumes the value of one if the facility is in the lowest quartile of quality in a given year. The coefficient on this measure captures differences in the characteristics of newly-admitted patients at "low-quality" facilities relative to all other facilities after 2012.[39]

Online Appendix Figure 4 presents results from this analysis. Across all measures, we do not find any systematic differences between the characteristics of the average patient admitted at a low-quality facility relative to all other facilities following the quality transparency regulation 2012. This implies that changes in patient selection are not responsible for our

[39] Although incumbents could also respond to the quality transparency regulation by increasing the level of drugs given to a patient to improve quality by "gaming" the measure of hemoglobin or, by increasing the amount of time a patient spends on the dialysis machine to improve quality by "gaming" the measure of URR, we view these responses as unlikely for two reasons. First, increasing the level of drugs to manage hemoglobin is costly to the facility, and the additional costs would not be reimbursed after 2012 due to the introduction of a single "bundled" reimbursement program in 2011 (Eliason et al., 2022). Second, prior literature finds a positive relation between an increase in the use of such drugs and the likelihood of hospitalizations (Eliason et al., 2020). Still our results suggest that the within-patient likelihood of hospitalization decreases at an incumbent facility when a new facility opens nearby, indicating that gaming through an increase in the use of drugs is not systematic, if it takes place. Moreover, even if gaming were prevalent after 2012, this behavior should work against us finding a relation between quality transparency and the location of competitors' new facility openings, since competitors should be able to see through such a strategy, leading to no association or even a positive association between quality scores and openings.

findings. Moreover, there is no evidence of a systematic difference in the mean GFR of patients at admission, indicating that facility's do not appear to game new patient admissions based on our previous instrument for quality.

6 Conclusion

Information transparency regarding product or service quality is often used by policymakers as a tool to discipline the actions of disclosing parties. In this study, we posit that, in addition to imposing discipline on the disclosing party's own behavior, transparency about product or service quality benefits consumers by incentivizing competitors to act on information about quality. Using a recent regulatory change that substantially increased transparency of healthcare quality in the kidney dialysis industry as a setting, we provide novel evidence that quality transparency influences strategic decisions by competitors, and that these decisions ultimately benefit patients. Using a generalized difference-in-differences design, we show that, under the new regime that requires public disclosure of information about dialysis facilities' quality, competitors are more likely to open new dialysis facilities near lower-quality incumbents. Conditional on entering into a local market, new entrants also locate new facilities at shorter distances to lower-quality incumbents.

We perform a number of tests to rule out potential alternative explanations stemming from the non-random nature of a facility's quality. First, we exploit the staggered addition and removal by CMS of sub-components of the total quality score as a source of exogenous variation in a facility's reported quality. This design isolates facility-level variation in the quality score driven purely by the reporting requirements. Second, we construct an instrument that relies on plausibly exogenous variation in physicians' preferences regarding the initiation of dialysis treatment. This variation is correlated with the quality score of the facilities where physicians refer patients to. In both cases, the effect on the quality score is uncorrelated with facility's choices but is relevant to competitors' entry decisions (due to effect on referrals). Our results continue to hold in both analyses. We also use a triple differences design that compares the effect of quality transparency on competitors' entry decisions in the presence versus absence of barriers to entry created by the Certificate of Need Laws. Quality transparency does not affect new entry decisions in states with Certificate of Need laws, whereas its effect increases in magnitude in the other states.

We also show that having competing dialysis providers open facilities nearby is costly for lower-quality incumbents. Referring physicians are less likely to refer new patients to lower-quality incumbent facilities following the increase in transparency. We also find that losing patients to better-quality facilities leads incumbents to invest more in improved pa-

tient care. For example, lower-quality incumbents increase the use of facility personnel who provide patients with better administrative and medical support. Finally, consistent with the increased investment in quality, we show that an increase in transparency, via enhanced competition, reduces the probability of hospitalization for patients at incumbent facilities.

Our results should be of interest to academics and policymakers. Our collective evidence suggests the presence of an understudied channel via which transparency into product and service quality not only informs patient and healthcare provider decisions, but also shapes the industrial organization of the healthcare sector by strengthening competition among rival healthcare providers. More broadly, our results highlight the important role of transparency regulation in promoting competition in healthcare markets.

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Appendix A. Number of Dialysis Centers in the US (by State) as of 2018

This table presents the number of outpatient dialysis facilities (by state) as of 2018, the most current year for data. Data for 2019 and beyond is not yet available from CMS. Superscript, *CON* identifies the eleven states with the Certificate of Need laws that affect the kidney dialysis industry.

State	2012	2018	State	2012	2018
Alabama^{CON}	142	181	Montana	12	16
Alaska^{CON}	8	9	Nebraska	37	40
Arizona	112	122	Nevada	44	50
Arkansas	63	71	New Hampshire	14	20
California	545	675	New Jersey	136	187
Colorado	68	80	New Mexico	38	56
Connecticut	44	51	New York	250	302
Delaware	23	31	North Carolina^{CON}	189	233
District of Columbia	22	22	North Dakota	16	16
Florida	361	484	Ohio	278	339
Georgia	298	371	Oklahoma	71	87
Hawaii^{CON}	23	32	Oregon	52	71
Idaho	26	30	Pennsylvania	269	316
Illinois^{CON}	249	329	Rhode Island^{CON}	16	16
Indiana	139	173	South Carolina	121	154
Iowa	65	69	South Dakota	21	28
Kansas	50	66	Tennessee	166	195
Kentucky	106	125	Texas	504	715
Louisiana	152	186	Utah	37	45
Maine^{CON}	17	18	Vermont^{CON}	8	8
Maryland	125	171	Virginia	142	201
Massachusetts	75	86	Washington^{CON}	77	97
Michigan	187	216	West Virginia^{CON}	35	47
Minnesota	101	122	Wisconsin	113	129
Mississippi^{CON}	76	91	Wyoming	9	10
Missouri	142	169			

Appendix B. ESRD Quality Incentive Program (QIP) 2012-2015

This chart presents a summary of the ESRD Quality Incentive Program (QIP) from 2012 to 2015. Source: https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/ESRDQIP

	PY 2012	PY 2013	PY 2014	PY 2015
Measures	• Hgb > 12 g/dL • Hgb < 10 g/dL • URR ≥ 65%	• Hgb > 12 g/dL • URR ≥ 65%	**3 Clinical** • Hgb > 12 g/dL • URR • VAT **3 Reporting** • NHSN • ICH CAHPS • Mineral Metabolism	**6 Clinical** • Hgb > 12 g/dL • VAT Measure Topic (fistula, catheter) • Kt/V Dialysis Adequacy Measure Topic (hemodialysis, peritoneal dialysis, pediatric hemodialysis) **4 Reporting** • NHSN • ICH CAHPS • Mineral Metabolism • Anemia Management
Performance Period	CY 2010	CY 2011	CY 2012	CY 2013
Comparison Period	N/A	N/A	July 1, 2010 – June 30, 2011	CY 2011 (**achievement**), CY 2012 (**improvement**)
Performance Standard	Lesser of the performance rate in CY 2007 OR the national performance rate in CY 2008	Lesser of the performance rate in CY 2007 OR the national performance rate in CY 2009	National Performance Rate (July 1, 2010 – June 30, 2011)	National Performance Rate (CY 2011)
Weighting	50% Hgb < 10 g/dL 25% Hgb > 12 g/dL 25% URR ≥ 65%	50% Hgb > 12 g/dL 50% URR ≥ 65%	Clinical: 90%, Reporting: 10% If facility has only one type of measure, that type is weighted at 100% of the score.	Clinical: 75%, Reporting: 25%
Minimum Data Requirements	11 cases for each measure	11 cases for each measure	Facility needs **either** (i) 11 cases for at least one clinical measure or (ii) to qualify for at least one reporting measure.	Facility needs **both** (i) 11 cases for at least one clinical measure and (ii) to qualify for at least one reporting measure. Note: The 11-case minimum now also applies to **reporting** measures.
Low-Volume Facility Score Adjustment	None	None	None	Applied to clinical measures with 11 – 25 cases
Max. Total Perform. Score	30 Points	30 Points	100 Points	100 Points
Min. Total Perform. Score	26 Points	30 Points	53 Points	60 Points
Payment Reduction Scale	0.5% – 2%, with a 0.5% reduction for every 5 points under the minimum TPS	1% – 2%, with a 0.5% reduction for every 5 points under the minimum TPS	0.5% – 2%, with a 0.5% reduction for every 10 points under the minimum TPS	0.5% – 2%, with a 0.5% reduction for every 10 points under the minimum TPS
Reporting Measures	N/A	N/A	• Facilities must complete certain requirements that vary by measure. • Facilities receiving CCN on or after July 1, 2012, can "opt in" for scoring on reporting measure(s) by completing requirements to earn 10 points.	• Facilities must complete certain requirements that vary by measure. • Facilities receiving CCN on or after July 1, 2013, are not scored on reporting measures. • Facilities receiving CCN on or after January 1, 2013, are not scored on the NHSN measure.

Appendix C. Key Variable Construction: New Competitors

To construct our main variable of interest, *NewNearestCompetitior*, we first use the address of each facility to determine the shortest distance between any two facilities. The nearest facility to the incumbent facility is then identified. Using data on opening years, we determine whether the nearest facility is new or not. If the nearest facility is new, we assign it a 1; and zero otherwise. The figure below illustrates this, where facility I is the incumbent and facility 5 is the new nearest competitor.

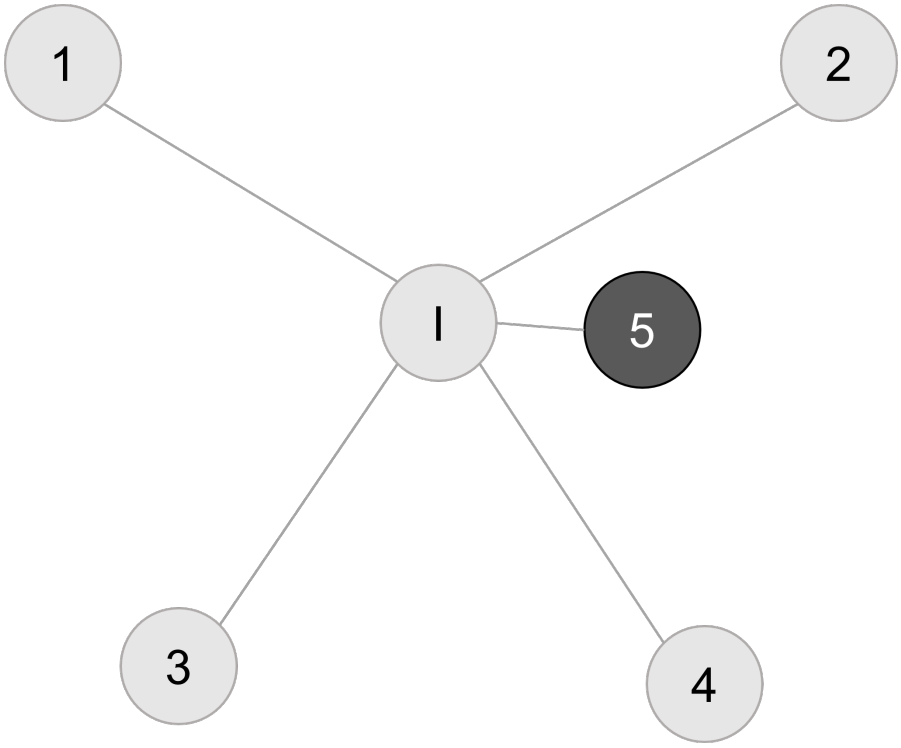


Figure 1. Identification Strategy for the Impact of Quality Transparency on New Nearby Facility Openings

This figure depicts our identification strategy for examining the effects of quality transparency on new nearby facility openings by competitors. Our main variable of interest, *Quality*, is a continuous variable from 0 to 100 in all years. In the post-period, we use actual quality scores published by CMS; in the pre-period we use publicly available data to estimate a quality score using the methodology we describe in Online Appendix D. Our dependent variable, *NewNearest* is a binary variable that takes the value of 1 if a nearby facility opens in year $t + 2$, and zero otherwise; thus, our identification examines whether quality scores published in year t are associated with new nearby facility openings two years later, since state-level approvals and certification by Medicare typically take about 18 months. We include a host of control variables described in the notes to Table 3. We also include year, and state or facility fixed effects.

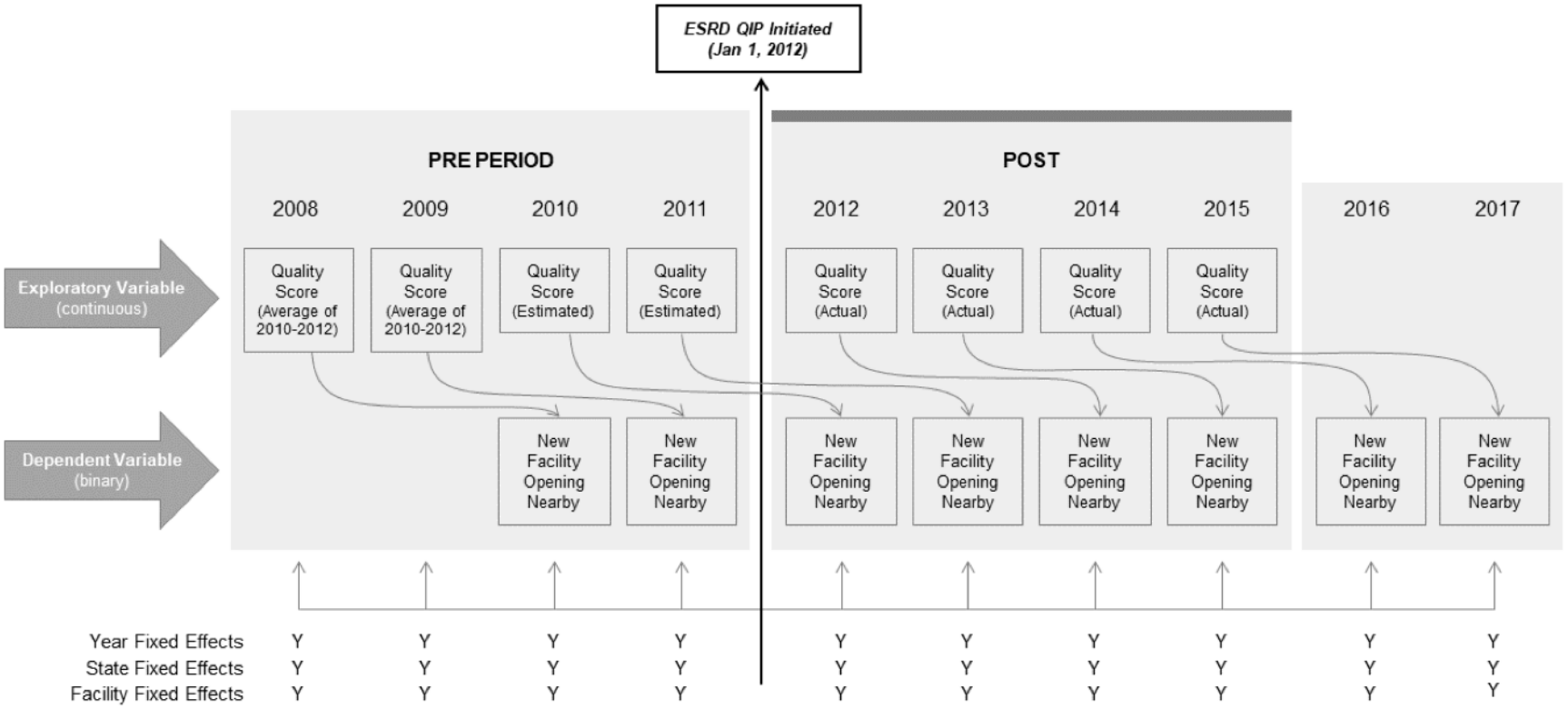


Figure 2. Pre- vs. Post-Quality Transparency

This figure depicts probability density functions for the Pre 2012 and Post 2012 sample periods. The x-axis displays the distance to the nearest (new) rival facility. Vertical dotted lines represent the median distance.

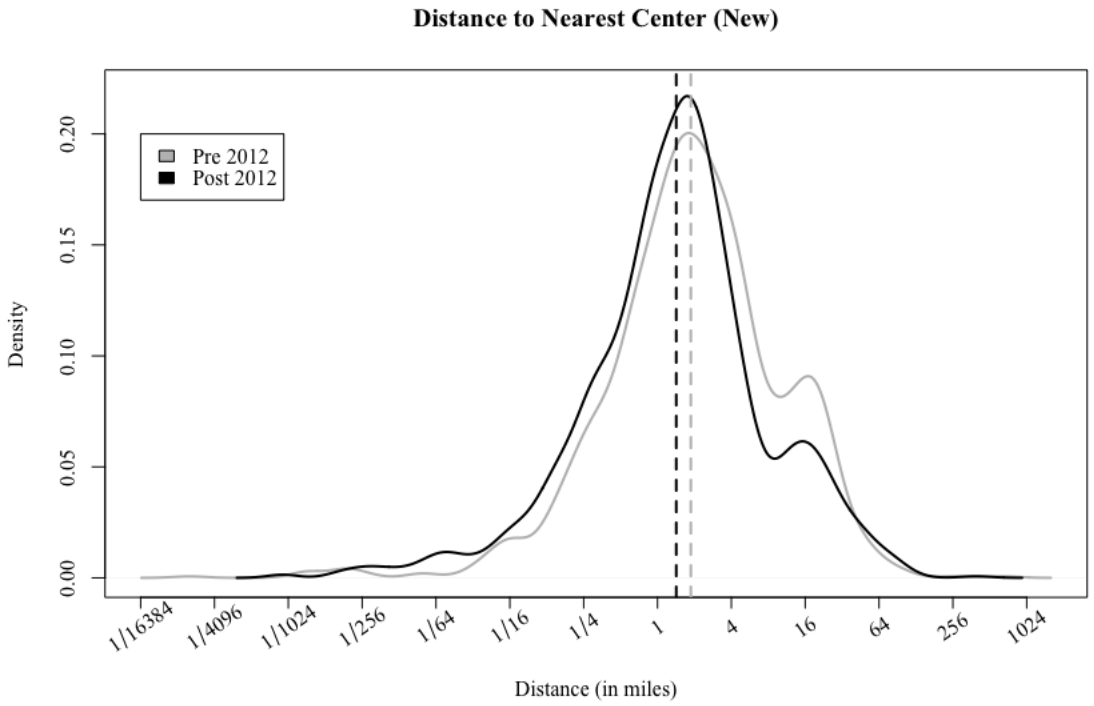


Figure 3. Variation of Total Performance Scores

This figure depicts box-and-whisker plots for the distribution of total performance scores by year. Boxes describe 75^{th}, 50^{th}, and 25^{th} percentiles. Whiskers describe scores 1.5 times the interquartile range. Dots represent facility-year scores below the lowest range of the whiskers (note that a single dot may represent several facilities with the same score).

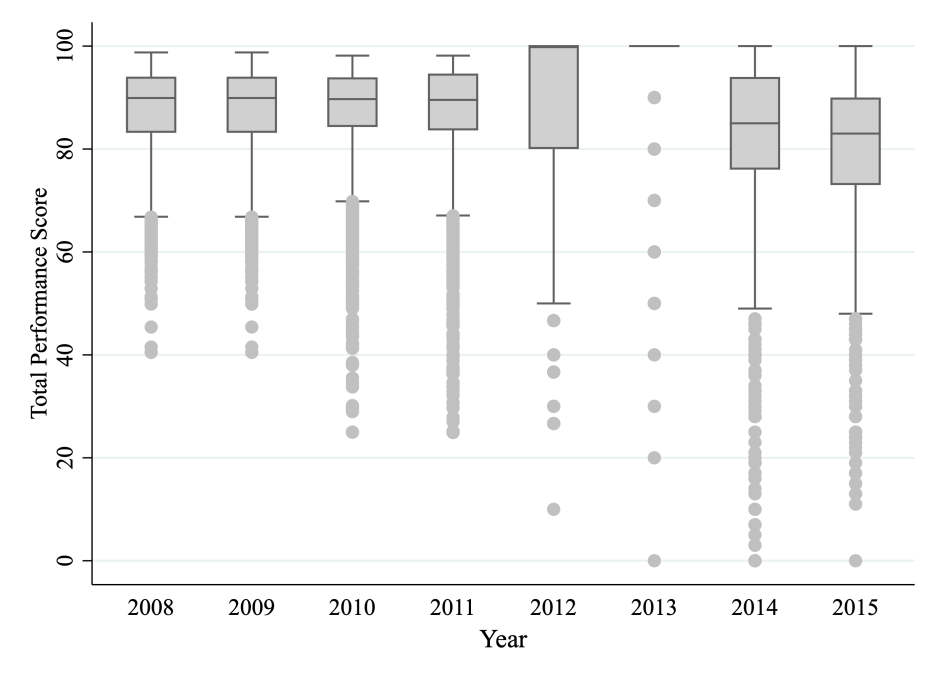


Figure 4. Dialysis Facility Openings Over Time

This figure plots the number of new dialysis facility openings over time based on the ownership of each facility.

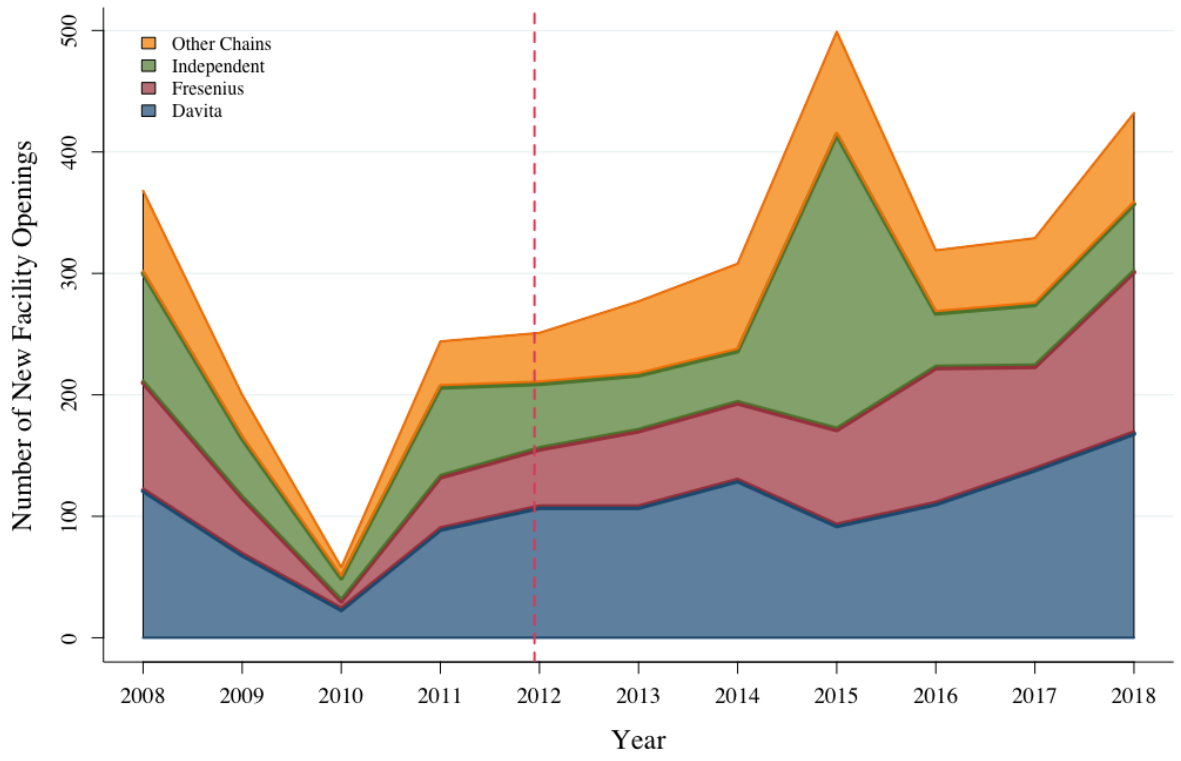


Figure 5. Trend Analysis of Quality on New Facility Openings

This figure plots the coefficients and 95-percent confidence intervals for the estimates based on equation (1). We use separate year-indicator variables so that the treatment effect can vary by year. Our exclusion year is 2011. Vertical dotted line represents the ESRD QIP intervention date.

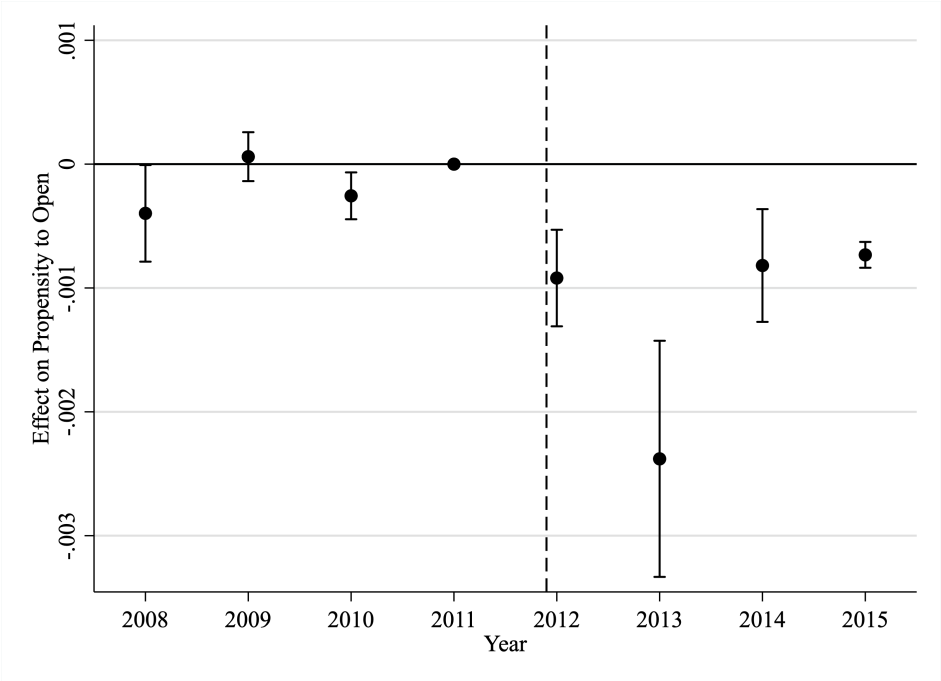
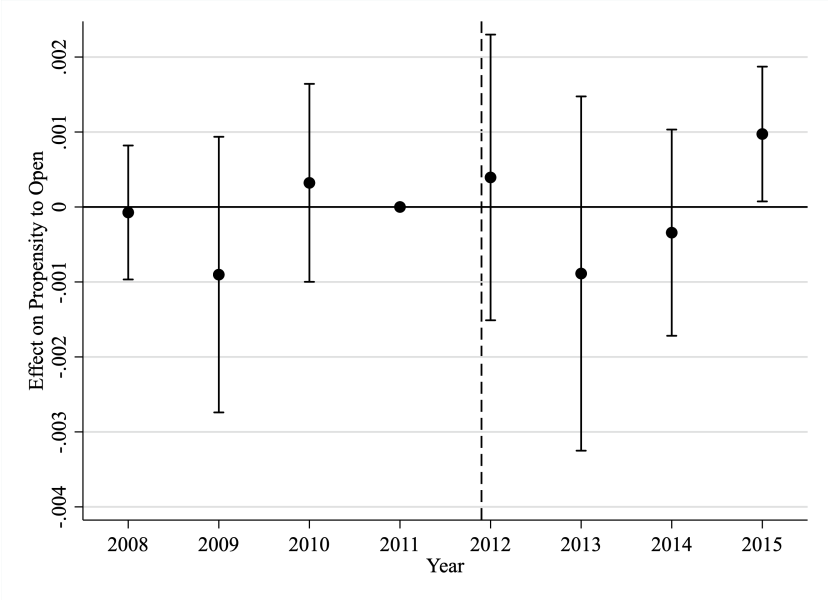


Figure 6. Trend Analysis of Quality on New Facility Openings: CON vs. Non-CON States

These figures plot the coefficients and 95-percent confidence intervals for the estimates based on equation (1) for CON and non-CON states. We use separate year indicator variables so that the treatment effect can vary by year. Our exclusion year is 2011. The vertical dotted line represents the ESRD QIP intervention date.

CON States



Non-CON States

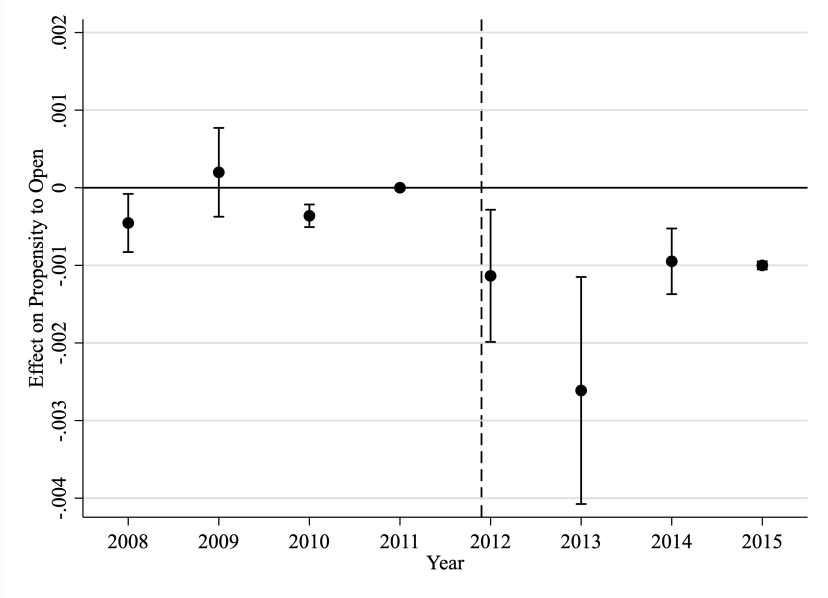


Table 1. Descriptive Statistics

This table depicts the descriptive statistics for our key variables. Panel A describes data at the facility level. Panel B describes data at the patient level. Panel C describes clinical, patient, and facility ownership data for low vs. high quality sub-samples, and for pre-2012 vs. post-2012 sub-samples. All variables are defined in Online Appendix I.

Panel A. Facility-Level Variables

Variable	N	Mean	5th	25th	Median	75th	95th
Dependent Variables							
NewNearestCompetitor	38,522	0.05	0.00	0.00	0.00	0.00	0.00
NewNearestCompetitor(≤5 miles)	38,522	0.04	0.00	0.00	0.00	0.00	0.00
Distance	9,452	4.73	0.51	2.28	4.49	7.13	9.43
NewPatients	40,674	19.95	5.00	11.00	18.00	26.00	42.00
ReferringPhysicians	20,689	1.92	0.00	0.00	1.00	3.00	7.00
Δ*Nurses*	37,011	0.13	-0.45	-0.13	0.04	0.27	1.00
Δ*ClinicalStaff*	37,218	0.18	-0.40	-0.12	0.02	0.21	1.00
Δ*SocialWorkers*	36,781	-0.04	-0.36	-0.07	0.01	0.13	0.46
Quality Variables							
Quality(Continuous)	38,522	87.30	62.00	81.30	90.00	97.00	100.00
Quality(Decile)	38,522	0.48	0.10	0.20	0.50	0.70	1.00
QualitySubscoreAddDrop	41,121	0.02	0.00	0.00	0.00	0.00	1.00
UnexpectedQuality	30,272	9.59	-15.32	3.65	12.41	18.89	23.87
BadGFR	29,715	0.34	0.00	0.00	0.00	1.00	1.00
Explanatory Variables							
Post	38,522	0.52	0.00	0.00	1.00	1.00	1.00
Control Variables							
Δ*NumDialysisPatients*	38,522	3.29	-31.34	-5.93	0.00	8.70	46.15
Rural	38,522	2.06	1.00	1.00	1.00	2.00	7.00
PRP	38,522	0.06	0.00	0.00	0.00	0.00	0.50

Panel B. Patient-Level Variables

Variable	N	Mean	5th	25th	Median	75th	95th
Dependent Variables							
Hospitalization	4,772,547	0.16	0	0	0	0	1
Explanatory Variables							
Post	4,772,547	0.43	0	0	0	1	1
Control Variables							
Chain	4,772,547	0.87	0	1	1	1	1
FacilityAge	4,772,547	17.64	5	9	16	24	37
DialysisDays	4,772,547	1884.17	79	482	1187	2447	6412
Age	4,772,547	61.62	34	52	63	73	84

Table 1. Descriptive Statistics (Continued)

Panel C. Descriptive Statistics By Quality

Variable	Low Quality Incumbents	High Quality Incumbents	Pre-2012	Post-2012
Clinical Characteristics (at admission)				
GFR	10.17	10.25	10.18	10.10
Hemoglobin	10.05	10.24	10.45	9.94
Demographics				
Male (%)	55.99	56.08	55.53	56.35
Non-Hispanic White (%)	46.12	49.77	48.50	47.06
Black (%)	37.25	29.18	32.83	33.21
Hispanic (%)	11.93	14.88	13.32	14.17
Asian (%)	2.58	2.97	2.73	3.01
Other Race (%)	2.12	3.19	2.62	2.56
Age (years)	62.17	62.32	62.15	62.48
Months with ESRD	42.10	41.03	38.81	44.25
Facility Ownership Proportions				
Davita	0.205	0.302	0.262	0.302
Fresenius	0.282	0.282	0.274	0.294
Independent	0.243	0.186	0.197	0.170
Other Chains	0.269	0.230	0.267	0.233

Table 2. Transparency and New Facility Openings

Panel A presents OLS regression analysis of new dialysis center openings as a function of quality scores interacted with the transparency regulation. Panel B uses the coefficient estimates from Panel A to calculate probabilities based on changes in facility scores, e.g., moving from the 75^{th} percentile score to the 25^{th} percentile score in our sample. In Panel A, the dependent variable, *NewNearest*, is an indicator variable that assumes the value of 1 if the closest facility to an incumbent opens in year $t+2$, and zero otherwise. The main variable of interest across all columns is the interaction $Post \times Quality$, where *Post* is an indicator variable that assumes the value of 1 if the total performance score was published in 2012 or beyond, and zero otherwise, and *Quality* is either a continuous variable (in columns 1 to 4) that represents the CMS's total performance score for a facility (with a range of 0 to 100) or its within-year decile rank (in columns 5 and 6). All regressions include *Rural*, $\Delta NumDialysisPatients$, and *PRP* as control variables. All variables are defined in Online Appendix I. Estimates in columns 1, 3, and 5 are from models specified without facility fixed effects; estimates from columns 2, 4, and 6 are from models specified with facility fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Main Results OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*NewNearest*	*NewNearest*	*NewNearest* ≤ 5 *miles*	*NewNearest* ≤ 5 *miles*	*NewNearest*	*NewNearest*
Quality Variable:	Continuous	Continuous	Continuous	Continuous	Decile	Decile
Quality	0.00032***	0.00058**	0.00016**	0.00046**	0.00837*	0.02055**
	(3.58)	(2.74)	(2.41)	(2.97)	(2.13)	(3.14)
Post × *Quality*	-0.00051***	-0.00049**	-0.00042***	-0.00050**	-0.01754**	-0.01471*
	(-4.49)	(-2.68)	(-3.62)	(-2.87)	(-2.55)	(-2.01)
PRP	0.00677	0.01206	0.00705	0.00973	0.01032	0.01047
	(0.73)	(1.27)	(0.62)	(1.03)	(1.25)	(1.34)
Rural	-0.00163*	0.00758	-0.00542***	0.00696	-0.00162***	0.00786
	(-2.28)	(0.60)	(-6.03)	(0.54)	(-4.60)	(0.63)
$\Delta NumDialysisPatients$	0.00001	0.00000	-0.00003*	-0.00002	0.00001	0.00000
	(0.23)	(0.08)	(-2.14)	(-0.78)	(0.21)	(0.10)
Year Fixed Effects	yes	yes	yes	yes	yes	yes
State Fixed Effects	yes	no	yes	no	yes	no
Facility Fixed Effects	no	yes	no	yes	no	yes
Adjusted R^2	0.00838	0.00244	0.01102	0.00726	0.00836	0.00251
Number of Observations	38,522	38,178	38,522	38,178	38,522	38,178

Panel B. Probabilities

	(1)		%Δ	(2)		%Δ
Percentile	75th	25th		95th	5th	
Score	97	81	-19%	100	62	-38%
Probabilities						
Pre2012	0.104	0.091	-11.8%	0.106	0.078	-26.4%
Post2012	0.087	0.092	6.2%	0.086	0.099	15.7%

Table 3. Transparency and Distance of New Facility Openings from Incumbents

This table presents OLS regression analysis of distance to incumbent as a function of quality interacted with the transparency regulation. The dependent variable, *Log(Distance)*, is the natural logarithm of the distance between a new facility and any incumbent facility within 10 miles. The main variables of interest across all columns are the interaction *Post* × *Quality*, where *Post* is an indicator variable that takes the value of 1 if the total performance score was published in 2012 or beyond, and zero otherwise. In columns (1) and (2), *Quality* is a continuous variable that represents the CMS's total performance score for a facility (with a range of 0 to 100), or, in columns (3) and (4), the total performance score's within-year decile rank. We include the same set of control variables as used in Table 2, as well as year, state, and county fixed effects. All variables are defined in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Log(Distance)*	*Log(Distance)*	*Log(Distance)*	*Log(Distance)*
Quality Variable:	Continuous	Continuous	Decile	Decile
Quality	0.00066	-0.00008	0.01851	-0.00784
	(1.38)	(-0.11)	(1.72)	(-0.37)
Post × *Quality*	0.00255***	0.00132***	0.09178***	0.03132 **
	(8.87)	(3.97)	(10.09)	(2.97)
Controls	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
State Fixed Effects	yes	no	yes	no
County Fixed Effects	no	yes	no	yes
Adjusted R^2	0.21240	0.28674	0.21212	0.28666
Number of Observations	9,449	9,248	9,449	9,248

Table 4. Heterogeneous Effects of Transparency on New Facility Openings

This table presents OLS regression analysis of new dialysis center openings as a function of quality of incumbent facilities interacted with the transparency regulation. Columns (1) and (2) present estimates of equation (1) using sub-samples for states without CON laws and with CON laws, respectively. The dependent variable, *NewNearest*, is an indicator variable that assumes the value of 1 if the closest facility to an incumbent opens in year $t+2$, and zero otherwise. The main variables of interest across all columns are the interaction terms *Post* × *Quality*, where *Post* is an indicator variable that takes the value of 1 if the total performance score was published in 2012 or beyond, and zero otherwise; and *Quality* is a continuous variable that represents the CMS's total performance score of a facility (with a range of 0 to 100). We include a set of control variables (as described in Table 2), as well as year and facility fixed effects. All variables are defined in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)		(2)
Dependent Variable:	*NewNearest*		*NewNearest*
Quality Variable:	Continuous		Continuous
Sample:	Non-CON		CON
Quality	0.00058***		0.00052
	(3.58)		(0.76)
Post × *Quality*	-0.00068**		0.00064
	(-3.44)		(1.18)
Controls	yes		yes
Year Fixed Effects	yes		yes
Facility Fixed Effects	yes		yes
Adjusted R^2	0.00110		0.01627
Number of Observations	32,703		5,475
Difference in coeff (Wald Test)		5.16*	

Table 5. Entry decisions and Addition or Removal of Quality Sub-components

This table presents regressions of new dialysis center opening indicators on facility-level changes in the reported total performance score resulting from the CMS's decisions to add or remove the underlying sub-components of the total quality score. The dependent variable, *NewNearest*, is an indicator that assumes the value of 1 if the closest facility to an incumbent opens in year $t + 2$, and zero otherwise. The main variable of interest, *QualitySubscoreAddDrop*, is an ordered categorical variable taking values of -1, 0, or +1, depending on whether the addition or removal of the quality score sub-component is beneficial or detrimental to a facility's total performance score in the first year the measure is added/removed. We discuss the construction of this measure in more detail in Online Appendix E. In both columns, we include a set of control variables (described in Table 2), as well as year and state fixed effects in column (1) and year and facility fixed effects in column (2). All variables are defined in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Dependent Variable:	*NewNearest*	*NewNearest*
Quality Variable:	Ordered Categorical	Ordered Categorical
QualitySubscoreAddDrop	-0.01225**	-0.01160**
	(-3.48)	(-2.98)
Controls	yes	yes
Year Fixed Effects	yes	yes
State Fixed Effects	yes	no
Facility Fixed Effects	no	yes
Adjusted R^2	0.00894	0.00223
Number of Observations	41,121	40,850

Table 6. Instrumental variable analysis: Quality Transparency and New Facility Openings

These tables present Instrumental Variable analysis of new dialysis center openings as a function of (instrumented) quality score interacted with the transparency regulation. Panel A reports our first-stage model. It regresses facility-level quality score on the instrument and control variables. The instrument, *BadGFR*, takes the value of one if a facility's average new patient GFR is outside of the 7 to 11 ml/min range, and zero otherwise. Column (1) reports the result without facility controls. In columns (2) and (3), we include the same set of control variables as used in Table 2, as well as *AverageAge*, *AverageBMI*, *NumPatients*, *ProportionFemale*, and *Comorbidities*. All variables are defined in Online Appendix I. Columns (2) and (3) include state fixed effects, and facility fixed effects, respectively. In all columns we include year fixed effects. Panel B reports our second-stage regression results, which rely on the instrumented facility quality from the first stage. Column (1) reports the OLS result from Table 2 for comparison. Columns (2)-(4) are based on the instrumented quality. Across all models, we include year fixed effects and facility fixed effects and the same control variables described above. All variables are defined in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. First Stage Regression

	(1)	(2)	(3)
Dependent Variable:	*Quality*	*Quality*	*Quality*
BadGFR	-0.713***	-0.513***	-0.368**
	(-4.37)	(-3.25)	(-3.41)
Year Fixed Effects	yes	yes	yes
Facility Controls	no	yes	yes
Facility Fixed Effects	no	no	yes
Adjusted R^2	0.153	0.529	0.644
F-Statistic	19.06	10.59	11.64
Number of Observations	40,371	29,715	29,715

Table 6. Instrumental variable analysis: Quality Transparency and New Facility Openings (Continued)

Panel B. Main Results IV

	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent Variable:	*NewNearest*	*NewNearest*	*NewNearest* ≤ 5 *miles*	*NewNearest*
Quality Variable:	Continuous	Continuous	Continuous	Decile
Quality	0.00058**	-0.01726*	-0.01180*	0.02242
	(2.74)	(-1.98)	(-2.10)	(1.30)
Post $\times$ *Quality*	-0.00049**	-0.00123**	-0.00103**	-0.03082**
	(-2.68)	(-2.85)	(-3.19)	(-2.37)
Facility Controls	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Facility Fixed Effects	yes	yes	yes	yes
Adjusted R^2	0.00244	0.00561	0.01663	0.00561
Number of Observations	38,178	29,715	29,715	29,715

Table 7. New Patients, Referrals and Quality Transparency

Panel A presents regression estimates of changes in new patients that join incumbent facilities after the opening of nearby dialysis facilities by competitors. Panel B presents regression estimates of changes in the number of referring physicians to incumbent facilities after the opening of nearby dialysis facilities by competitors. In column (1) of Panels A and B, we consider the opening of nearby dialysis facilities regardless of distance to the incumbent. In column (2) of Panels A and B, we consider new facilities that open within 5 miles of the incumbent. In all columns, we require a new facility to open before June 30^{th} in a given year. In Panel C, we present regression model estimates of natural logarithm of new patients for incumbent facilities when market entry is not required. In all models, we control for the age of the incumbent facility and for the change in the number of dialysis patients in the county. All variables are defined in Online Appendix I. We also include year and facility fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. New Patient Behavior after Market Entry

	(1)	(2)
Dependent Variable:	*NewPatients*	*NewPatients*
Quality Variable:	Continuous	Continuous (New entrant within 5 miles)
Post × *NewNearest* × *Quality*	0.076**	0.101**
	(2.22)	(2.56)
Controls	yes	yes
Year Fixed Effects	yes	yes
Facility Fixed Effects	yes	yes
Adjusted R^2	0.705	0.705
Number of Observations	40,674	40,674

Panel B. Physician Referral Behavior after Market Entry

	(1)	(2)
Dependent Variable:	*Number of Referring Physicians*	*Number of Referring Physicians*
Quality Variable:	Continuous = New entrant quality score minus incumbent quality score	Continuous = New entrant (within 5 miles) quality score minus incumbent quality score
Post × *NewNearest* × *Quality*	0.036	0.073***
	(1.75)	(9.97)
Controls	yes	yes
Year Fixed Effects	yes	yes
Facility Fixed Effects	yes	yes
Adjusted R^2	0.817	0.817
Number of Observations	20,689	20,689

Table 7. New Patients, Referrals and Quality Transparency (Continued)

Panel C. Elasticities

	(1)	(2)	(3)
Dependent Variable:	*Log(NewPatients)*	*Log(NewPatients)*	*Log(NewPatients)*
Quality Variable:	Log(Quality)	Log(Quality)	Log(Quality)
Log(Quality)	-0.126	-0.131	-0.151
	(-1.62)	(-1.44)	(-1.71)
Post × *Log(Quality)*	0.158*	0.167*	0.168*
	(2.06)	(1.95)	(1.85)
First-time Patients	yes	yes	no
Switching Patients	yes	no	yes
Controls	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Facility Fixed Effects	yes	yes	yes
Adjusted R^2	0.707	0.672	0.473
Number of Observations	45,650	45,405	43,170

Table 8. Quality Transparency Effects on Patient Hospitalizations

This table presents OLS regression analysis of patient-level hospitalizations as a function of incumbents' quality. The dependent variable, *Hospitalization* is an indicator that takes the value of one if a patient treated at an incumbent facility gets hospitalized, and zero otherwise. *dQuality* is defined as either the difference between a new entrant's and incumbent's quality scores, or as a binary variable that takes the value of 1 if the new facility has a higher quality score relative to the incumbent, and zero otherwise (columns 1 and 3). We retain only new facilities that open before June 30^{th} in a given year. In columns (3) and (4), we restrict our sample of new facility openings within 5 miles of the incumbent. In all columns, we include the same set of control variables as used in Table 2, as well as *FacilityAge* and *Chain*. All variables are defined in Online Appendix I. We also include patient and year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the year and at the facility levels, respectively. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Hospitalization*	*Hospitalization*	*Hospitalization*	*Hospitalization*
Quality Variable:	1 = New entrant has better quality	Continuous = New entrant quality score minus incumbent quality score	1 = New entrant (within 5 miles) has better quality	Continuous = New entrant (within 5 miles) quality score minus incumbent quality score
Post × *NewNearest* × *dQuality*	-0.0178**	-0.000483**	-0.0150*	-0.000506***
	(-2.44)	(-5.12)	(-1.95)	(-4.32)
Facility Controls	yes	yes	yes	yes
Patient Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Adjusted R^2	0.0800	0.0800	0.0800	0.0800
Number of Observations	4,508,340	4,508,340	4,508,340	4,508,340

Table 9. Quality Transparency and Facility Inputs

This table presents estimates from an OLS regression of changes in staffing levels at incumbent facilities. We measure changes using staffing levels in the year after a new facility opening relative to the year before an opening. In all columns, *dQuality* is a binary variable that takes the value of 1 if the new facility has a higher quality score relative to the incumbent; and zero otherwise. We control for the age of the incumbent facility and for the change in the number of dialysis patients in the county. We also include year and facility fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) $\Delta Nurses$	(2) $\Delta Clinical\ Staff$	(3) $\Delta SocialWorkers$
$Post \times NewNearest \times dQuality$	0.610***	0.105	0.807**
	(3.54)	(0.30)	(3.21)
Controls	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Facility Fixed Effects	yes	yes	yes
Adjusted R^2	0.105	0.158	0.105
Number of Observations	37,011	37,218	37,422

Online Appendix

Quality Transparency and Healthcare Competition

This appendix contains additional analyses and details referenced in our paper, and is organized as follows:

- Construction of yearly panel of data in OA.A.
- Patient data in OA.B.
- Pre-2012 score methodology in OA.C.
- Alternative pre-2012 score methodology OA.D.
- Variation in quality measures in OA.E.
- Instrumental variable analysis in OA.F.
- Physician referrals data information in OA.G.
- Determinants model in OA.H.
- Variable definitions in OA.I.
- Threat of entry in OA.J.
- ESRD QIP Certificate in OA Figure 1.
- Timeline in OA Figure 2.
- Patient Referrals in OA Figure 3.
- Changes in Patient Mix in OA Figure 4.
- Table OA.1. Sample Construction.
- Table OA.2. Alternative Pre-period Scores.
- Table OA.3. Acquisitions.
- Table OA.4. Placebo Analysis.
- Table OA.5. Determinants Model.
- Table OA.6. Alternative Specification of Transparency Effects on Facility Inputs.

OA.A. Construction of Main Data Set

This appendix provides additional details on how we construct our main data set for determining whether quality transparency affects where firms open new dialysis facilities. For our analysis, we use End-Stage Renal Dialysis Quality Incentive Program (ESRD QIP) annual files and archived Dialysis Facility Compare (DFC) quarterly files, both located on the Centers for Medicare & Medicaid Services (CMS) website. From these data sets, we collect facility-level Total Performance Scores and identify new facility openings.

Total Performance Scores

Our "Pre" period consists of the years 2008 to 2011. For 2010 and 2011 (i.e., our "Pre" period), CMS published data but did not calculate total performance scores. We use the method explained in more detail in Online Appendix C to estimate performance scores using data from DFC quarterly files. For 2008 and 2009, CMS did not publish data so we conservatively use, for both 2008 and 2009, the three-year average score of the facility (calculated from 2010 to 2012). Our "Post" period consists of the years 2012 to 2015. For these years, we use total performance scores calculated and published by CMS in the ESRD QIP annual files. However, because scores in 2012 and 2013 are out of 30, we convert them to out of 100, using the formula TPS/30 * 100, to match how CMS presented scores in 2014 and 2015. Note that we end our analysis in 2015 due to data limitations, which we discuss in more detail in the 'New Facility Openings' section below.

New Facility Openings

We use the ESRD QIP files beginning in 2010 through to 2017 to identify new facility openings. New facilities will appear in the ESRD QIP files after they are certified by Medicare. We can also confirm that the facility is a new opening based on the certification date, which is also published. As we have shown in Figure 1, we expect that performance scores in year t will lead to openings in year $t + 2$, since firms must receive state-level approvals and certification by Medicare. However, because data published in the ESRD QIP files are based off data from two calendar years earlier, we cannot view 2017 openings until CMS publishes the data in 2019. We therefore limit our Post analysis to openings up to and including the calendar year 2017.

OA.B. Patient Data Set

We obtain patient-level data from the United States Renal Data System. The USRDS is funded by the National Institute of Diabetes and Digestive and Kidney Diseases and by the National Institute of Health. The USRDS collects and warehouses patient- and facility-level data related to chronic kidney disease. Through an approved research proposal, we obtained access to the set of Standard Analysis Files (SAFs), which contain the complete treatment history for all patients included in the USRDS database. Also included is the patients' demographic information, including information submitted by providers at the patient's onset of ESRD. Such information includes the patient's sex, race, BMI, cause of ESRD, hemoglobin levels, glomerular filter rate (GFR), comorbidities, residential ZIP code, and the facility. Thus, the USRDS data allows us to match a patient to a facility and observe within-patient treatment across time.

Patient Flows

The richness of the USRDS data allows us to identify, at the patient level, when and at which facility a patient initiates dialysis. We can also identify when and to which facility a patient transfers to, should they begin receiving care at a new facility (although we do not know the reason for transferring). For each facility in our sample, we count the number of new patients initiating dialysis in a given year and call them "first-time" patients. We also count the number of new patients at a facility that have previously received care at a different facility and call them "switching" patients. For our analysis, we combine first-time and switching patients and create the variable *NewPatients*; however, we also conduct tests where we separate the two types.

Patient-level Health Outcomes Analysis

We use hospitalizations (all causes) for our analysis of patient-level health outcomes. Hospitalization data are obtained from institutional claims, which we also obtain from USRDS.

OA.C. Pre-2012 Total Performance Score Calculation

We use fitted linear regression models to estimate Total Performance Scores for each dialysis center for 2010 and 2011 (i.e., the "pre" ESRD QIP period). To do so, we first estimate the relation between each measure (outlined below) and the corresponding performance sub-score using a linear model and data from 2012. For example, to estimate the relation between 'Percent of Medicare patients who have average hemoglobin value less than 10.0 g/dL' in 2012 and the $Hgb < 10$ sub-score in 2012, we use a fitted linear model and data from 2012. We then use the coefficient results from this estimation, along with facility-level data from 2010 and 2011, to predict each facility's $Hgb < 10$ score in 2010 and 2011. We repeat this estimation procedure for the two remaining sub-scores (outlined below). Finally, we weigh and linearly combine the estimated sub-scores to generate estimated Total Performance Scores.

In 2012, CMS used three quality measures were used to generate Total Performance Scores:

1. Percent of Medicare patients who have an average hemoglobin value less than 10.0 g/dL in the facility listed.

2. Percent of Medicare patients who have an average hemoglobin value greater than 12.0 g/dL in the facility listed.

3. Percentage of hemodialysis patients with a URR information $\geq 65\%$ in the facility listed.

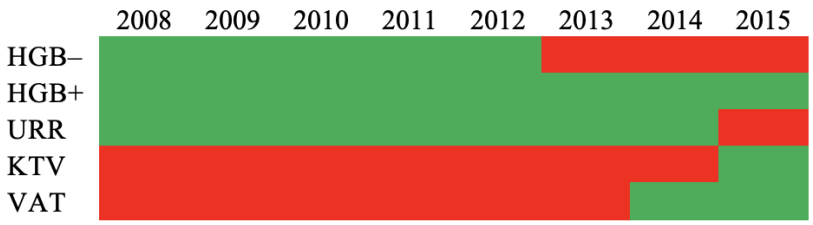
Each measure was used to generate a performance sub-score. These scores were then weighted and summed to form Total Performance Scores for each center. Although these same measures were publicly available in years prior to 2012, performance scores based on these measures were not generated in those years.

OA.D. Alternative Method of Calculating Pre-2012 Total Performance Score

We also estimate facility-level quality scores from 2008 to 2011 (i.e., the "pre" ESRD QIP period) using a limited sample of patient-level data. Specifically, we use patient-level quality input measures obtained from patients during their first visit to a facility. Using these data, we attempt to replicate the methodology that CMS applies in 2012, e.g., by using the same input measures and weights, to calculate facility-level scores. Having only data collected during a patient's first visit to the facility restricts us from being able to exactly replicate the method that CMS uses for computing quality scores, since CMS uses measures collected from all patient visits during the year. To put this in perspective, we estimate that a facility with 75 patients will conduct nearly 12,000 dialysis sessions in one year, and data collected during these 12,000 sessions will be used by CMS to compute the facility quality score. In contrast, our patient-level data allows us, at most, to compute quality scores using 0.625% of total dialysis sessions (e.g., 75/12,000). Consequently, throughout the paper, we continue to apply the methodology described in Online Appendix C for calculating facility-level quality before 2012.

OA.E. Variation in Quality Measures across Time

The figure below depicts, across time, the addition and subtraction (by CMS) of measures that make up the quality score—where green indicates when the measure is "active" and red indicates when the measure is "inactive." We use the addition/subtraction of measures to estimate the effect of an exogenously-induced change in quality score on the propensity of competitors to open new facilities. As such, while our analysis spans a different time period (e.g., 2008 to 2015), it follows the staggered methodology introduced in Bertuzzi et al. (2021).

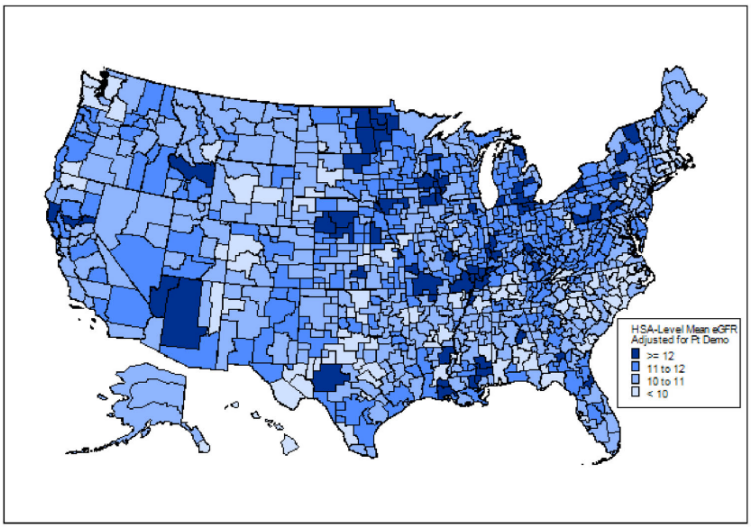


To conduct this analysis, we construct a +1/0/-1 measure that assumes one of these values as follows. First, if a new measure is added or an existing measure is removed such that it benefits a facility's quality score, we code it as +1. To determine whether a facility benefits from the addition or subtraction of the measure, we sort all facilities into quartiles, based on the score they receive for each measure. For example, if the facility is in the top quartile of a measure, indicating high quality, then we code it as +1, since the addition of the measure was beneficial to the facility. Similarly, if the facility is in the bottom quartile of a measure, indicating low quality, then we also code it as a +1 if the measure is subtracted, since the subtraction of that measure was beneficial to the facility. In contrast, we code a -1 if a facility performs in the top quartile and the measure was dropped by the regulator. We also code a -1 if a facility performs in the bottom quartile and that measure was added by the regulator. For facilities that perform in the middle two quartiles for a measure, we code a 0, regardless if the measure is added or subtracted. Note that we apply this methodology in only the first year the measure is added or subtracted, to ensure we are capturing exogeneously-induced quality scores. Finally, we sum the assigned +1, 0, -1 for every component measure that was either added or subtracted, giving us us our aggregate sub-score measure, *QualitySubscoreAddDrop*.

OA.F. Instrumental Variable Analysis

Our IV strategy uses a patient's glomerular filtration rate (GFR) at the initiation of dialysis to instrument for the quality of a facility. GFR is a measure of how well the kidneys are functioning, and is used by doctors to determine whether the kidneys have failed. A person with healthy kidneys generally has a GFR of 85 to 135 mL/min/1.73 m2 of body surface area, and this value decreases naturally with age. But a person with chronic kidney disease often experiences a larger decrease in GFR. Although doctors also look for other symptoms, guidelines suggest that dialysis should be initiated when GFR is below 10 mL/min.

Despite these guidelines, experts and doctors alike don't always agree on the best time to start or even how long to wait before initiating dialysis treatment. For example, van de Luijtgaarden et al. (2012) surveyed nephrologists in Europe and reported that the median doctor recommended initiating dialysis at a GFR of 10, but that the range of responses included GFR values of 5 to 20. Similarly, a study in Canada revealed that, of nearly 26,000 patients studied, roughly one-third initiated dialysis above the recommended GFR of 10.5, and the sample mean was 15.5 Clark et al. (2011). In the United States, a recent study showed similar variation in the GFR of patients at the initiation of dialysis, and suggested that several factors, including the characteristics of nephrologists, influenced the timing of initiation (Scialla et al., 2014). Specifically, the figure below, obtained from the Scialla et al. (2014) study, depicts the variation (by GFR) in the timing of dialysis by Health Service Area after demographic adjustment.



Indeed, Scialla et al. (2014) use GFR as instrument for mortality rates in the dialysis industry, given this variation in physicians' dialysis initiation practice patterns. Collectively,

this evidence supports the idea that the variation in GFR at initiation is at least partly due to the variation in preferences and judgments of nephrologists. In our setting, this variation in preferences is useful for identifying the effect of quality scores on the decision of competitors to open new facilities nearby low quality incumbents.

Specifically, variation in physician's preferences induces exogenous variation in quality scores through the relation between GFR and hemoglobin (Hgb) — a key subcomponent of the quality score. This relationship is documented in studies that show that, at lower levels of GFR (e.g., below 60), GFR and Hgb are positively correlated (e.g., Levin et al., 1999; Astor et al., 2002). Since patients with Hgb levels greater than 12 or less than 10 negatively impact the quality score of the facility directly through either of these two subcomponent measures of quality score, physicians who recommend initiating dialysis early or late based on the patient's GFR measure can influence the quality score of the facility.

To take advantage of this physician-induced quality, we use the slope of the relationship between GFR and Hgb to identify the values of GFR at which Hgb is 10 and 12 (i.e., the lower and upper values of Hgb outside of which a facility is penalized with a lower quality score) and then construct an indicator variable, *BadGFR*, which assumes the value of one if GFR is above or below these levels, indicating that Hgb will be predictably too low or too high. Notably, our lower and upper GFR values are consistent with values of GFR that the prior medical literature considers to be the points at which the initiation of dialysis is "late" and "early." To construct our measure, we use the mean GFR for all new patients initiating dialysis in a given year at a given facility to construct our binary measure. We obtain the measure of GFR at the onset of ESRD—i.e., the level of GFR at which the referring nephrologist initiates the patient's dialysis treatment—from the set of SAFs.

OA.G. Physician Referrals

In this appendix, we describe how we match physician referral data to our main data set. Physician referrals are obtained from the CMS website (https://www.cms.gov/Regulations-and-Guidance/Legislation/FOIA/Referral-Data-FAQs). The data are organized in annual files. For a given year, there are four files: 30-day interval; 60-day interval; 90-day interval; and 180-day interval. Each file contains two National Provider Identifier (NPI) numbers; one is for the referring provider (e.g., a doctor, clinic, hospital, or laboratory) and one is for the healthcare provider (e.g., dialysis facility). The NPI is a 10-digit number that uniquely identifies a healthcare provider throughout the United States. Individuals or organizations apply for NPIs through the CMS National Plan and Provider Enumeration System.

However, since the CMS files only contain NPIs, we next use the NPI lookup tool provided at the Health and Human Services (HHS) website (https://npiregistry.cms.hhs.gov/) to systematically check all NPIs in the CMS files against the registry. This process enables us to identify nephrologists in the referrals data. To match NPIs to dialysis facilities, we use online searches (e.g., the facility's website; and other dialysis facility NPI databases). For each NPI that we locate, we go back to the HHS registry database to confirm it is indeed the correct NPI for that specific facility.

In addition to providing NPI numbers, the interval files show, at an aggregate level, how many patients have claims data for two NPIs within the same 30-day interval, 60-day interval and so on. CMS considers these matches to be indicative of referrals. For example, in our setting, a patient visits a nephrologist who provides services and, if needed, refers the patient to a dialysis facility. The provision of services by the doctor and by the facility are counted as a referral. Based on our discussions with nephrologists, it is likely that patients will begin dialysis very soon after diagnosis, i.e., within 60 days of their visit to the nephrologist; thus, we use the 60-day files for our analysis.

We use nephrologist-facility connections to observe referral behavior over time. For example, we can identify whether a nephrologist, who referred patients to an incumbent facility, begins referring patients to a new facility.

OA.H. Determinants of Quality Model

Another way to address the non-random variation in quality scores is to explicitly model the determinants of quality in the first stage and use the unexpected variation in the second stage to analyze rivals' entry decisions. To construct predicted quality, we first regress quality scores on the variables that comprise the socioeconomic index commonly used in the medical sciences literature to examine whether neighborhood of residence predicts incidences of various diseases (e.g., coronary heart disease). Most recently, Boyle et al. (2020) use the index to test whether the neighborhood context influences the risk of chronic kidney disease (CKD), which is the precursor to dialysis treatment. We use these socioeconomic factors—in addition to facility-level variables, including the age of the facility and its ownership status (independently owned versus a part of a chain), as well as year, state, and facility fixed effects in our first-stage model. Specifically, we regress quality scores on:

Neighborhood Socioeconomic Factors

- Median value of occupied housing units
- Percent of persons $>$ 25 years old with at least a bachelor's degree
- Percent of persons with management, professional, and related occupation
- Median household income
- Percent of households with interest, dividends, and net rental income

We also include in the model the facility's age, to capture possible across-facility differences in age of equipment and medical technology, as well as a variable *(Chain)* to capture quality differences that might be explained by whether the facility is independent or owned by a large operator of a chain of facilities. Notably, this latter variable effectively picks up changes in ownership, e.g., when an independently-owned facility is acquired by a chain, which can impact changes in quality as shown in Eliason et al. (2020).

We use the difference between the predicted and actual quality score to construct *UnexpectedQuality*, which then becomes the main variable that we interact with *Post* in a second stage.

The results from modeling the determinants of healthcare quality are presented in Online Appendix Table 5, column (1). The determinants of quality jointly explain 58.3% of variation in the total quality scores, which is an economically large portion. The estimates are in line with prior studies. Most notably, quality declines with facility age and increases with average income in the market serviced by a facility.

In the second stage, we use the first-stage quality model residuals and re-estimate equation (1). We present the results in Online Appendix Table 5, columns (2) and (3), with and without facility fixed effects, respectively. The evidence is consistent with the results reported in Table 2. For example, after controlling for 58% of quality variance, the coefficient on the $Post \times UnexpectedQuality$ in column (2) is -0.00042 (t-statistic -6.86), whereas the corresponding coefficient in Table 2 is -0.00051 (t-statistic -4.49). This suggests that our main result is only slightly affected by controlling for previously omitted factors that jointly explain a large portion of variation in quality. Further, to the extent that selection on observables serves as a useful reference point for the degree of a possible selection of unobservables (Altonji et al., 2005), this result suggests that the results are unlikely to be entirely attributable to the unobservable factors.

OA.I. Variable Definitions

Variable	Definitions
Dependent Variables	
NewNearestCompetitor	Indicator variable that equals one if the nearest dialysis facility to the facility of interest opens two years following the release of the facility of interest's Total Performance Score report, and zero otherwise.
Log(Distance)	Continuous variable that equals the natural logarithm of 1+distance to an incumbent facility within 10 miles of the new facility. We repeat this calculation for all incumbent facilities within 10 miles.
NewPatients	Continuous variable that equals the total number of patient referrals from nephrologists to a dialysis facility
Number of Referring Physicians	Continuous variable that equals the number of an incumbent facility's referring physicians.
Hospitalization	Indicator variable that equals one if a given patient was hospitalized for any amount of time two years following the release of their dialysis facility's Total Performance Score report, and zero otherwise.
Δ*Nurses*	Continuous variable that equals the change in the number of registered and licensed practitioner nurses at a facility.
Δ*ClinicalStaff*	Continuous variable that equals the change in the number of technicians and nurse aides at a facility.
Δ*SocialWorkers*	Continuous variable that equals the change in the number of social workers and dietitians at a facility.
Explanatory Variables	
Quality	Represents one of two measures of quality. The first is a continuous variable that equals the standardized Total Performance Score in a given year of ESRD QIP data or DFC data. The second is a within-year decile rank.
QualitySubscoreAddDrop	Continuous variable that equals the sum of pluses and minuses a facility receives when we code the impact, on quality score, of the addition or removal of the subcomponents (by CMS) that make up quality score. We code a +1 if adding or dropping a measure is beneficial to a facility's quality score. We code a -1 if adding or dropping a measure is detrimental to a facility's quality score. We determine 'benefit' and 'detriment' using quartiles of the subscore; where the middle two quartiles are coded as 0 (i.e., no benefit or detriment to being added or dropped).
UnexpectedQuality	Continuous variable that equals the difference between the actual quality score and the predicted quality score.
Post	Indicator variable that equals one if the facility's Total Performance Score was disclosed in 2012 or beyond, and zero otherwise.

OA.I. Variable Definitions (Continued)

Variable	Definitions
Facility Control Variables	
$\Delta NumDialysisPatients$	Continuous variable that equals the change in the number of patients who received treatment for end-stage kidney disease as reported by USRDS's ESRD Incident Count tool. This measure is calculated at the county level.
Rural	Ordinal variable that classifies a zip code on a scale of 1-10 based on measures of population density, urbanization, and daily commuting at the US census tract-level. On this scale, 1 is considered the most metropolitan/urban, while 10 is considered the most rural.
PRP	Continuous variable that equals the percent (expressed as a decimal) of withheld Medicare payments to a facility based on their quality score and the guidelines set out by the ESRD Quality Incentive Program.
Chain	Indicator variable that equals one if the facility is part of a chain of dialysis facilities (e.g. DaVita, Fresenius), and zero otherwise.
FacilityAge	Continuous variable that equals the age of the facility.
Aggregated Patient Control Variables	
AverageAge	Continuous variable that equals the average age of newly admitted dialysis patients in a given year.
AverageBMI	Continuous variable that equals the average body mass index (BMI) of newly admitted dialysis patients in a given year.
NumPatients	Continuous variable that equals the number of newly admitted dialysis patients in a given year.
ProportionFemale	Continuous variable that equals the proportion of newly admitted dialysis patients who are female in a given year.
Instruments	
BadGFR	Indicator variable that equals one if the average glomuerular filtration rate (GFR) of newly admitted patients in a given year is greater than 11 or less than 7, and zero otherwise. GFR is calculated using the CKD-EPI equation.
Patient-level Control Variables	
BiologicalSex	Indicator variable that equals one if the patient is biologically male, and zero otherwise.
Race	Categorical variable that takes nine different values depending on the identified race of the patient. Categories of race include White, Middle Eastern, Black, American Indian/Alaskan Native, Asian (from East and Southeast Asia), Indian, Pacific Islander, Other/Multiracial, Unknown.

OA.I. Variable Definitions (Continued)

Variable	Definitions
Ethnicity	Categorical variable that takes five different values depending on the identified ethnicity of the patient. Categories of ethnicity include Hispanic-Mexican, Hispanic Other, Non-Hispanic, Hispanic Non-Specified, Unknown.
Age	Continuous variable that equals a patient's age.
DialysisDays	Continuous variable that equals the number of days that a patient has been receiving dialysis treatment.
Comorbidities	A series of 33 indicator variables (one for each comorbidity) that each equals one if a patient suffers from the specified comorbidity. Comorbidities include (but are not limited to) HIV, COPD, and cancer.
Control Variables for Determinants of Quality	
Log(HomeValue)	Continuous variable that equals the natural log of the median value of occupied housing (measured at the county level).
Log(Income)	Continuous variable that equals the natural log of the median household income (measured at the county level).
Dividends	Continuous variable that equals the percent of households with interest, dividends, or net rental income (measured at the county level).
Bachelors	Continuous variable that equals the percent of people with at least a bachelor's degree (measured at the county level).
Management	Continuous variable that equals the percent of people with a management, professional, and related occupation (measured at the county level).

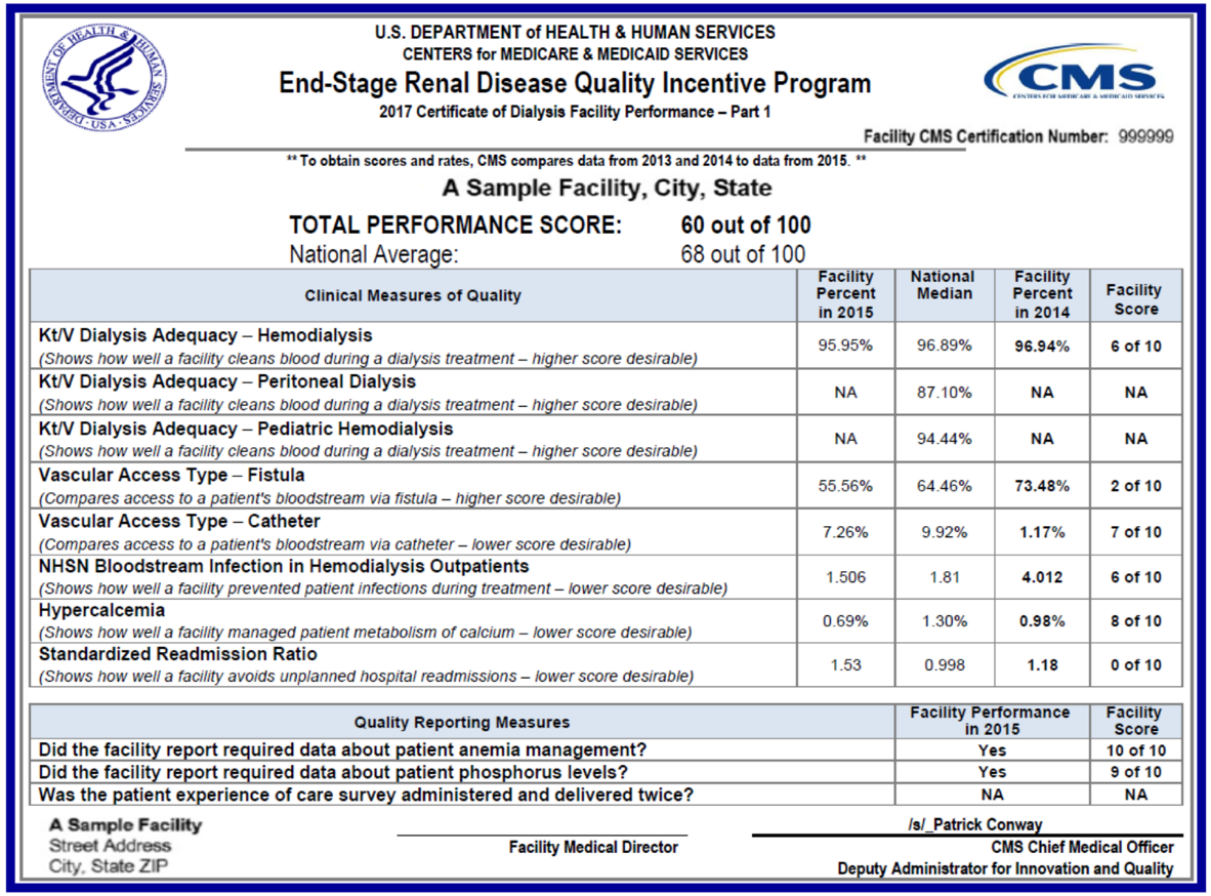
OA.J. Threat of Entry

Goolsbee and Syverson (2008) show that incumbents in the airline industry preemptively respond to changes in the threat of entry. In our setting, if transparency increases the threat of entry for low-quality incumbents, facility-level responses are likely to occur much earlier than what we document for the actual entry. Our data allow us to construct a measure of the threat of entry Bresnahan and Reiss (1991). Specifically, we use detailed facility-level data on variable and fixed costs, along with data on dialysis-treatment prices, to estimate the average number of patients needed for a facility to break even in a given county in a given year and then use this measure, in combination with data on the total number of dialysis patients in the county, to calculate the estimated number of facilities a county can support in a given year. The difference between the estimated number of facilities the area can support and the number of existing facilities, all scaled by the estimated number of facilities the area can support, provides us with a continuous measure of threat of entry that varies by county and year. We use this measure in an OLS specification that regresses our measure of hospitalizations on quality. The results presented in the table below show that low-quality incumbents appear to respond to a threat of entry after the transparency regime is implemented. In particular, for those facilities facing a high threat of entry (e.g., the top quartile), we find that the likelihood of within-patient hospitalizations decreases for incumbents with quality below the median level of quality in a given year.

	(1)
Dependent Variable:	*Hospitalizations*
Quality Variable:	1 = Facility quality score is below within-year median score
Quality	0.00222**
	(2.39)
Post × *Quality*	-0.00321*
	(-1.81)
Patient Controls	yes
Year and Facility Fixed Effects	yes
Adjusted R^2	0.0392
Number of Observations	3,990,364

OA. Figure 1. Sample Certificate

Presented below is a quality performance certificate that is required to be prominently displayed in kidney dialysis facilities across the US beginning 2012.



U.S. DEPARTMENT of HEALTH & HUMAN SERVICES
CENTERS for MEDICARE & MEDICAID SERVICES

End-Stage Renal Disease Quality Incentive Program

2017 Certificate of Dialysis Facility Performance – Part 1

Facility CMS Certification Number: 999999

** To obtain scores and rates, CMS compares data from 2013 and 2014 to data from 2015. **

A Sample Facility, City, State

TOTAL PERFORMANCE SCORE: 60 out of 100

National Average: 68 out of 100

Clinical Measures of Quality	Facility Percent in 2015	National Median	Facility Percent in 2014	Facility Score
Kt/V Dialysis Adequacy – Hemodialysis *(Shows how well a facility cleans blood during a dialysis treatment – higher score desirable)*	95.95%	96.89%	**96.94%**	**6 of 10**
Kt/V Dialysis Adequacy – Peritoneal Dialysis *(Shows how well a facility cleans blood during a dialysis treatment – higher score desirable)*	NA	87.10%	**NA**	**NA**
Kt/V Dialysis Adequacy – Pediatric Hemodialysis *(Shows how well a facility cleans blood during a dialysis treatment – higher score desirable)*	NA	94.44%	**NA**	**NA**
Vascular Access Type – Fistula *(Compares access to a patient's bloodstream via fistula – higher score desirable)*	55.56%	64.46%	**73.48%**	**2 of 10**
Vascular Access Type – Catheter *(Compares access to a patient's bloodstream via catheter – lower score desirable)*	7.26%	9.92%	**1.17%**	**7 of 10**
NHSN Bloodstream Infection in Hemodialysis Outpatients *(Shows how well a facility prevented patient infections during treatment – lower score desirable)*	1.506	1.81	**4.012**	**6 of 10**
Hypercalcemia *(Shows how well a facility managed patient metabolism of calcium – lower score desirable)*	0.69%	1.30%	**0.98%**	**8 of 10**
Standardized Readmission Ratio *(Shows how well a facility avoids unplanned hospital readmissions – lower score desirable)*	1.53	0.998	**1.18**	**0 of 10**

Quality Reporting Measures	Facility Performance in 2015	Facility Score
Did the facility report required data about patient anemia management?	**Yes**	**10 of 10**
Did the facility report required data about patient phosphorus levels?	**Yes**	**9 of 10**
Was the patient experience of care survey administered and delivered twice?	**NA**	**NA**

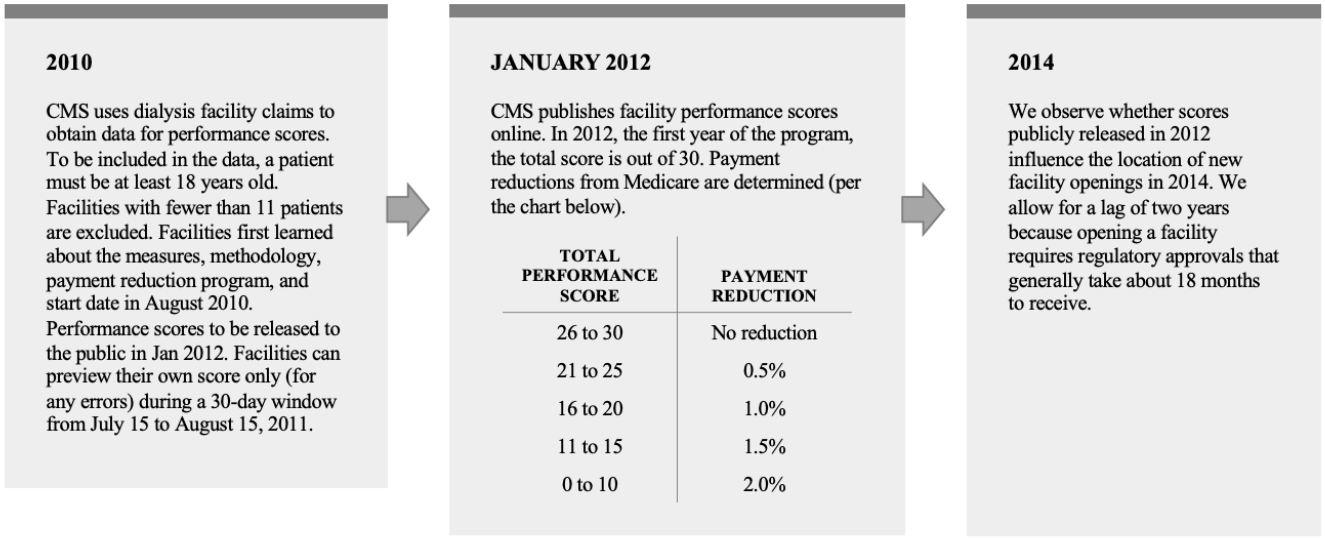
A Sample Facility
Street Address
City, State ZIP

Facility Medical Director

/s/_Patrick Conway
CMS Chief Medical Officer
Deputy Administrator for Innovation and Quality

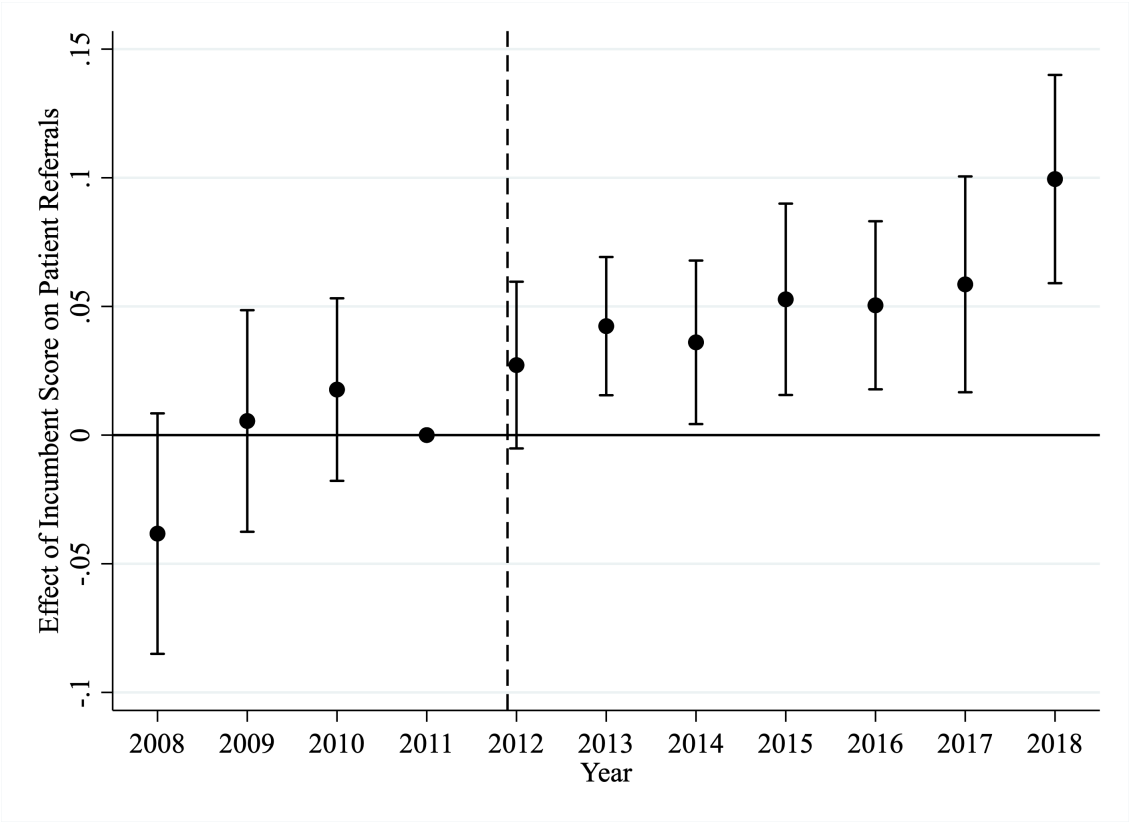
OA. Figure 2. Timeline

This diagram displays the timeline from the year data is collected by CMS, to the year that the total performance scores are calculated by CMS, to the year that we expect to observe openings. For the purpose of this diagram only, we restrict the timeline to 2010 (year of data) to 2014 (year of opening).



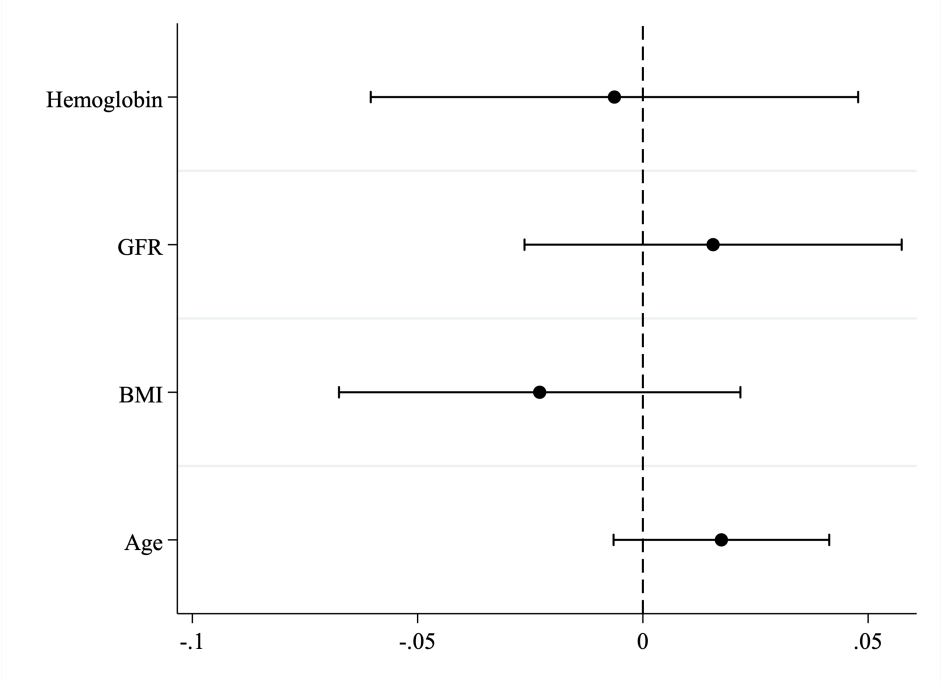
OA. Figure 3. Patient Flows

This figure plots the coefficients and 95-percent confidence intervals from estimates of equation (4) for Panel A of Table 7. We include separate year indicator variables. Our exclusion year is 2011. Vertical dotted line represents the ESRD QIP intervention date.



OA. Figure 4. Changes in Patient Mix

This figure depicts difference-in-differences estimates of changes in patient characteristics on quality, using characteristics recorded at initial admission to the facility. We present the coefficient of interest from the interaction term, *Post* x *Quality*, where *Quality* is an indicator variable that assumes the value of one if a facility is in the lowest quartile of quality in a given year. For ease of interpretation, we standardize values to mean = 0 and standard deviation = 1.



OA.Table 1. Sample Construction

This table presents the sample selection construction for our full sample of facility-year observations.

Description	Observations
All facility-year observations (2008 to 2015)	45,089
Less: Missing data for Total Performance Scores	(4,718)
Less: Missing data to calculate *NewNearestCompetitor*	(1,727)
Less: Missing data for control variables	(122)
Full sample	38,522

OA.Table 2. Transparency Effects on the Location of New Facility Openings (Alternate Pre-period Score Construction)

This table presents results from OLS regression models of the location of new dialysis center openings by competitors on quality scores. With the exception of the *Quality* variable in these models, the regressions are identical to those estimated in Table 2. In the current table, we construct a pre-period measure of *Quality* using the method described in Online Appendix D. All variables are described in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the year and the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) *NewNearest*	(2) *NewNearest*	(3) *NewNearest* ≤ 5 *miles*	(4) *NewNearest* ≤ 5 *miles*	(5) *NewNearest*	(6) *NewNearest*
Quality Variable:	Continuous	Continuous	Continuous	Continuous	Decile	Decile
Quality	0.00057*	0.00049	0.00014	0.00032	0.01281*	0.01237
	(1.97)	(1.19)	(0.90)	(1.01)	(2.12)	(1.32)
Post × *Quality*	-0.00077**	-0.00041	-0.00040*	-0.00039	-0.02210**	-0.00653
	(-2.45)	(-0.81)	(-2.04)	(-0.97)	(-2.64)	(-0.50)
PRP	0.00678	0.01340	0.00705	0.01053	0.01038	0.01212
	(0.74)	(1.50)	(0.66)	(1.22)	(1.27)	(1.66)
Rural	-0.00166*	0.03010	-0.00548***	0.02925	-0.00165***	0.03025
	(-2.10)	(1.01)	(-6.39)	(0.98)	(-3.97)	(1.01)
Δ*NumDialysisPatients*	0.00001	0.00001	-0.00003*	-0.00002	0.00001	0.00001
	(0.38)	(0.35)	(-2.10)	(-0.81)	(0.37)	(0.35)
Year Fixed Effects	yes	yes	yes	yes	yes	yes
State Fixed Effects	yes	no	yes	no	yes	no
Facility Fixed Effects	no	yes	no	yes	no	yes
Adjusted R^2	0.00824	0.00203	0.01090	0.00691	0.00824	0.00206
Number of Observations	38,124	37,768	38,124	37,768	38,124	37,768

OA.Table 3. Transparency Effects on the Acquisition of Incumbent Facilities

This table presents results for OLS regression models of acquisitions of incumbent facilities on quality scores. The dependent variable, *ChangeOwnership*, is an indicator that assumes that value of 1 if an incumbent facility experiences an ownership change; and zero otherwise. The main variables of interest across all columns are the interaction terms $Post \times Quality$; where *Post* is an indicator variable that assumes the value of 1 if the total performance score was published in 2012 or beyond, and zero otherwise; and *Quality* is either a continuous variable (in columns 1 and 2) that represents the CMS's quality score of a facility (with a range of 0 to 100) or a within-year decile rank (in columns 3 and 4). We include year fixed effects in all models and vary the inclusion of state fixed effects (in columns 1 and 3) or facility fixed effects (in columns 2 and 4). Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	*ChangeOwnership*	*ChangeOwnership*	*ChangeOwnership*	*ChangeOwnerhsip*
Quality Variable:	Continuous	Continuous	Decile	Decile
Quality	0.00014	0.00021	0.00275	0.00790
	(0.46)	(0.44)	(0.22)	(0.51)
Post × *Quality*	-0.00076***	-0.00072***	-0.02970***	-0.02898**
	(-9.43)	(-11.02)	(-4.03)	(-3.80)
Year Fixed Effects	yes	yes	yes	yes
State Fixed Effects	yes	no	yes	no
Facility Fixed Effects	no	yes	no	yes
Adjusted R^2	0.01828	0.03629	0.01824	0.03624
Number of Observations	29,602	29,226	29,602	29,226

OA.Table 4. Placebo Analysis: Changing the Year of the Regulation

This table presents coefficient estimates from our main variable of interest, $Post \times Quality$ from equation (1) when we change the Post to equal one if the year is 2009, 2010, 2011, 2013, 2014, or 2015 and beyond. Quality is the continuous measure we use in columns (1) and (2) of Table 3. Controls variables and fixed effects are the same as those specified in equation (1). Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the year and the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Year	$Post \times Quality$
2009 (Placebo)	0.00001
2010 (Placebo)	-0.00027
2011 (Placebo)	-0.00028
2012 (Actual)	-0.00051***
2013 (Placebo)	-0.00049***
2014 (Placebo)	-0.00029***
2015 (Placebo)	-0.00014

OA.Table 5. Determinants of Quality

This table presents results from a two-stage model. In stage 1 (presented in column 1) we present results from an OLS model that regresses quality scores on a set of determinant variables. In stage 2, presented in columns (2) and (3), we provide estimates for equation (1), using the residual values from stage 1 as our measure of quality. Column (2) excludes (Column (3) includes) facility fixed effects. All variables are defined in Online Appendix I. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	Stage 1	Stage 2	
Dependent Variable:	*Quality*	*NewNearest*	*NewNearest*
Quality Variable:		Continuous (actual minus predicted)	Continuous (actual minus predicted)
UnexpectedQuality		0.00028**	0.00037
		(2.57)	(1.59)
Post × *UnexpectedQuality*		-0.00042***	-0.00035*
		(-6.86)	(-2.27)
PRP		0.01235	0.01525
		(1.09)	(1.42)
Rural		-0.00127	0.01466
		(-0.89)	(0.53)
Δ *NumDialysisPatients*		-0.00004	-0.00002
		(-1.15)	(-0.64)
Log(HomeValue)	-0.701		
	(-0.40)		
Log(Income)	4.102**		
	(2.34)		
Dividends	0.029		
	(0.55)		
Bachelors	0.090		
	(1.45)		
Management	0.020		
	(0.58)		
FacilityAge	-0.198**		
	(-2.83)		
Chain	0.436		
	(1.13)		
Year Fixed Effects	yes	yes	yes
State Fixed Effects	no	yes	no
Facility Fixed Effects	yes	no	yes
Adjusted R^2	0.583	0.00865	0.00098
Number of Observations	44,613	30,272	29,980

OA.Table 6. Alternative Specification of Transparency Effects on Facility Inputs

These tables present estimates using alternative specifications to test the effects of quality transparency and market entry on facility inputs. In Panel A, we present results for estimates of changes to facility inputs measured two years after a competitor opens a facility nearby. In Panel B, we present results for estimates of equation (6) when we scale the number of patient-care staff by the number of dialysis machines. In all columns, *Quality* is a binary variable that takes the value of 1 if the new facility has a higher quality score relative to the incumbent; and zero otherwise. We control for the age of the incumbent facility and for the change in the number of dialysis patients in the county. We also include year and facility fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered two ways at the year and at the firm levels. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Changes to Facility Inputs (Two Years after Opening)

Dependent Variable:	(1) $\Delta Nurses$	(2) $\Delta Clinical\ Staff$	(3) $\Delta SocialWorkers$
$Post \times NewNearest \times dQuality$	0.730**	0.260	1.716**
	(3.15)	(0.92)	(2.53)
Controls	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Facility Fixed Effects	yes	yes	yes
Adjusted R^2	0.188	0.111	0.114
Number of Observations	37,014	37,221	37,425

Panel B. Transparency Effect on Station-Scaled Facility Inputs

Dependent Variable:	(1) $\Delta Nurses$ $PerStation$	(2) $\Delta Clinical\ Staff$ $PerStation$	(3) $\Delta SocialWorkers$ $PerStation$
$Post \times NewNearest \times dQuality$	0.220	0.103	0.021**
	(1.56)	(0.63)	(2.60)
Controls	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Facility Fixed Effects	yes	yes	yes
Adjusted R^2	0.690	0.759	0.666
Number of Observations	36,444	36,669	36,866