How Acquisitions Affect Firm Behavior and Performance: Evidence from the Dialysis Industry*

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Abstract

Many industries have become increasingly concentrated through mergers and acquisitions, which in health care may have important consequences for spending and outcomes. Using a rich panel of Medicare claims data for nearly one million dialysis patients, we advance the literature on the effects of mergers and acquisitions by studying the precise ways in which providers change their behavior following an acquisition. We base our empirical analysis on more than 1,200 acquisitions of independent dialysis facilities by large chains over a twelve-year period and find that chains transfer several prominent strategies to the facilities they acquire. Most notably, acquired facilities converge to the behavior of their new parent companies by increasing patients' doses of highly reimbursed drugs, replacing high-skill nurses with less-skilled technicians, and waitlisting fewer patients for kidney transplants. We then show that patients fare worse as a result of these changes: outcomes such as hospitalizations and mortality deteriorate, with our long panel allowing us to identify these effects from within-facility or within-patient variation around the acquisitions. Because overall Medicare spending increases at acquired facilities, mostly as a result of higher drug reimbursements, this decline in quality corresponds to an unambiguous decline in value for payers. We conclude the paper by considering the channels through which acquisitions produce such large changes in provider behavior and outcomes, finding that increased market power cannot explain the decline in quality. Rather, the adoption of the acquiring firm's strategies and practices drives our main results, with greater economies of scale for drug purchasing responsible for more than half of the change in profits following an acquisition.

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1 Introduction

Health-care markets have become increasingly concentrated through mergers and acquisitions (Gaynor et al., 2015). Proponents of this industry trend cite several potential benefits of consolidation, including lower costs through economies of scale and better patient outcomes through coordinated care. But greater concentration may also result in higher prices or lower quality (Gaynor and Town, 2012; Cuellar and Gertler, 2006; Dafny et al., 2012). Previous studies of this topic typically consider fairly broad notions of market structure and outcomes — by showing, for instance, that more-concentrated hospital markets have higher mortality rates. Comparatively less work has examined the precise channels through which mergers and acquisitions ultimately lead to changes in outcomes. In this paper, we use detailed claims and facility data from the U.S. dialysis industry to show directly how large chains transfer their corporate strategies to the independent facilities they acquire, which consequently has a large effect on the cost and quality of care.

We focus our study on the U.S. market for outpatient dialysis — a medical procedure that cleans the blood of patients suffering from end-stage renal disease (ESRD) — because it offers several distinct advantages as an empirical setting for this topic. First, dialysis is a fairly standardized treatment that allows for a direct comparison of providers. Second, the dialysis industry has become increasingly concentrated following a series of mergers and acquisitions: today, dialysis is provided primarily by multi-establishment, for-profit firms, with the share of independently owned and operated dialysis facilities falling from 86% to 21% over the past three decades and the two largest publicly traded corporations, DaVita and Fresenius, now owning over 60% of facilities and earning over 90% of the industry's revenue (United States Renal Data System, 2014; Baker, 2019). Third, detailed Medicare claims and clinical data allow us to identify important changes in providers' behavior and patients' outcomes following an acquisition. Finally, the dialysis industry is an important market to study in and of itself, with total Medicare reimbursements for treating the nation's 430,000 dialysis patients amounting to about $33 billion each year, or 6% of total Medicare expenditures.

We find that acquired facilities alter their treatments to increase reimbursements and decrease

costs. One important way facilities capture higher payments from Medicare is by increasing the amount of drugs they administer to patients, for which Medicare paid providers a fixed per-unit rate during our study period. The most notable of these is Epogen (EPO), a drug used to treat anemia, which represented the single largest prescription drug expenditure for Medicare in 2010, totaling $2 billion (U.S. Government Accountability Office, 2012). Perhaps reflecting the profits at stake, patients' EPO doses increase 129% at independent facilities acquired by large chains. Similarly, acquired facilities increase their use of the iron-deficiency drug Venofer relative to Ferrlecit, a perfect substitute that offers lower reimbursements. On the cost side, large chains replace high-skill nurses with lower-skill technicians at the facilities they acquire, reducing labor expenses. Facilities also increase the patient-load of each employee by 11.7% and increase the number of patients treated at each dialysis station by 4.5%, stretching resources and potentially reducing the quality of care received by patients.

Adopting the acquiring firm's operational strategies directly affects patients' outcomes and Medicare's expenditures. Patients at acquired facilities are 4.2% more likely to be hospitalized in a given month, while the survival rate for new patients falls by 1.3-2.9% depending on the time horizon. In addition, new ESRD patients who start treatment at an acquired facility are 8.5% less likely to receive a kidney transplant or be added to the transplant waitlist during their first year on dialysis, a reflection of worse care because transplants provide both a better quality of life and a longer life expectancy than dialysis. Other measures of clinical quality are mixed, at best. Using hemoglobin levels to assess the quality of anemia management, we find that although patients are 12.2% less likely to have hemoglobin values that are too low post acquisition, they are also 10.0% more likely to have hemoglobin values that are too high and 5.1% less likely to have hemoglobin values within the recommended range.[1] The only outcome for which we find unequivocal evidence of increased quality at acquired facilities is the urea reduction ratio, a measure of the waste cleared during dialysis, with patients at acquired facilities becoming 1.8% more likely to have adequate clearance levels. Despite the compelling evidence that patients receive worse care following an acquisition, acquired facilities increase their per-

[1]These do not net to 0 because they are relative effects. Percentage point values net to 0.

treatment Medicare reimbursements by 6.9%, resulting in $301.7 million in additional spending for Medicare throughout our sample compared to total spending of $4.5 billion.

As in much of the merger-effects literature, our findings may face multiple threats to identification, as acquisitions do not occur randomly and acquired facilities likely differ from those not acquired in important, potentially unobservable ways. For instance, acquired facilities may systematically alter the types of patients they treat after being taken over, in which case the differences in outcomes we attribute to changes in ownership may actually stem from changes in a facility's demographics. Likewise, chains may disproportionately target facilities located in areas that have more lucrative patients, potentially biasing our estimates of how reimbursements change following an acquisition. We overcome these challenges by leveraging the uniquely detailed nature of our data. Unlike many claims data sets, we have repeated measures of patients' clinical outcomes and precise measures of their conditions' severity, allowing us to mitigate concerns about a changing mix of patients. Additionally, the length of our panel allows us to observe patients with the same characteristics being treated at the same facility before and after acquisition, permitting us to identify the effects of an acquisition solely from within-facility changes in ownership. Finally, in many cases we can estimate specifications with patient fixed effects that control for any time-invariant patient characteristics, meaning that the main effects we estimate come only from the changes induced by the acquisition.

After establishing these results, we next examine the mechanisms through which acquisitions affect firm behavior. We first consider whether an acquisition's effect on market power can explain the changes we observe for patient outcomes, as would be predicted by standard models of regulated markets with endogenous product quality (e.g., Gaynor (2004) and the models discussed therein). With prices set administratively for Medicare patients, these models predict that a facility facing more competition in its market would offer higher-quality care to attract more patients, given the assumption that demand is elastic with respect to quality. In dialysis, however, this assumption fails to hold: patients are not responsive to changes in quality and rarely switch facilities (for many reasons, but mainly due to high travel costs). We therefore find similar qualitative and quantitative results across all of our outcome measures when comparing

acquisitions that increased market concentration to those that did not. As such, changes in market power cannot explain the decline in dialysis quality that occurs after a takeover, which implies that the strategy of the acquiring chain, rather than the subsequent concentration of the market, largely determines how patients fare following an acquisition.

Because an increase in local market power does not explain the changes we observe among independent facilities following an acquisition, we next consider alternative explanations for why independent facilities do not typically imitate the more-profitable strategies used by the large chains before being acquired. Although we assess a host of possible reasons, only two withstand scrutiny. First, and most importantly, the largest for-profit chains benefit from greater economies of scale, such as the volume discounts they receive when purchasing injectable drugs. We find that just over 50% of the increase in profits following an acquisition can be explained by higher EPO doses, for which the acquiring chains have a higher profit margin due to the lower wholesale costs they negotiate with the manufacturer. That is to say, even in the event that an independent facility chose to emulate the higher EPO doses of the large chains, it would earn only 55% of the chains' profits due to its higher costs. Second, we find some limited evidence that the effects of an acquisition are more pronounced at non-profit facilities compared to for-profit facilities, suggesting that the explicit mandate to maximize profits at these for-profit acquirers may lead them to sacrifice patient outcomes in favor of higher reimbursements, particularly in regards to injectable drugs.

These results contribute to several bodies of literature. The first studies the effects of mergers and acquisitions, both in health care and more generally.[2] Much of this literature has focused on how mergers affect prices through changes in market power. In health care, these studies have primarily considered hospital mergers, broadly finding that they result in higher prices paid by insurers (e.g., Dafny et al., 2016; Dafny, 2009; Gowrisankaran et al., 2015).

The literature examining the effects of mergers and acquisitions on quality is more limited.[3]

[2]This is an extensive literature that cannot be fully reviewed here. For a thorough review in the context of health care, see Gaynor et al. (2015).

[3]This stands in contrast to a relatively large number of papers that study the effect of market concentration on hospital quality without focusing explicitly on mergers and acquisitions (e.g., Kessler and McClellan, 2000; Gaynor et al., 2013).

Even in regulated markets, the net effect is theoretically ambiguous. On the one hand, standard models without merger efficiencies (e.g., Gaynor, 2004) show that acquisitions leading to increased market power reduce the incentive to deliver high-quality care. Bloom et al. (2015) find empirical support for this by showing that U.K. public hospitals improve their quality when patients can more easily switch from low-quality to high-quality providers.[4] On the other hand, mergers that result in efficiency gains, such as through economies of scale, may lead to higher-quality care.

Outside the hospital industry, research on how mergers and acquisitions affect quality is similarly sparse. The few studies covering this topic include Prince and Simon (2017), who use flight-level data to examine how U.S. airline mergers affect on-time performance, and Fan (2013), who uses a structural model to simulate the impact of consolidation on price and quality in the newspaper industry. We extend this literature by directly tying the changes in quality to the corresponding changes in firm behavior following acquisitions, which is possible due to our uncommonly detailed data on firm behavior.

Given the growing trend of "roll-up" strategies, where large firms gradually increase their market share by acquiring many of their much-smaller competitors, understanding the impact of acquisitions on quality has become increasingly important. This "whale eats krill" pattern of consolidation has occurred in industries as varied as physician practices (Capps et al., 2017) and funeral homes (Wollmann, 2018), as well as packaged ice companies, breweries, hairdressers, vending machines, medical devices (Dunn, 2016), automotive suppliers (Kocourek et al., 2000), solar power (*Seeking Alpha*, 2015), and many others (*The Economist*, 2015).

Our paper contributes to the somewhat limited literature on how these types of acquisitions enable firms to transfer their strategies and processes following changes in corporate control. Studying this topic within the context of early twentieth century Japanese cotton mills using detailed data similar to what we use for dialysis, Braguinsky et al. (2015) find that acquired firms become more profitable due to both better inventory management and greater capacity utilization. Natividad (2014) conducts a related study of a large fishing firm that acquired some

[4]More directly, Ho and Hamilton (2000) compare quality measures at hospitals before and after being acquired or merging with another hospital, finding that quality deteriorates along some dimensions following acquisition, especially in more-concentrated markets. Hayford (2012) and Capps (2005) also investigate the direct impact of mergers on hospital quality.

of its suppliers, finding that total factor productivity increased among the newly integrated ships. To the best of our knowledge, the only other paper to study this topic in a health-care setting is Capps et al. (2018), who find that the cost of services increase after hospitals acquire physician groups, largely because the hospitals exploit payment rules more aggressively. This is analogous to what we find for injectable drugs at acquired facilities, although Capps et al. focus solely on where physicians bill for services and do not consider changes in firms' input choices or the implications for patients' outcomes. In our setting, we show how treatment changes along many dimensions after an acquisition, and that these changes result in worse outcomes for patients.[5] Our paper is also related to Eaton et al. (2018), who show that private equity buyouts in higher education lead to higher tuition and per-student debt, while schools with private equity owners capture more government aid. Similar to what we show for dialysis acquisitions, Eaton et al. find that many measures of school quality decline following a takeover, as reflected by lower educational inputs, graduation rates, loan repayment rates, and earnings among graduates.

Understanding how managerial practices and corporate strategies are transferred following an acquisition may be particularly important in the health-care sector, as the adoption of new practices may affect welfare by directly changing the processes through which care is delivered.[6] For example, Dranove and Shanley (1995) hypothesize that hospital systems may benefit from a reputation for within-system standardization, which may motivate mergers. By standardizing processes across locations, along with pricing and quality, hospitals may reduce the burden faced by patients when they search for a provider. Additionally, some view the standardization of medical practices as a potential path for improving the overall quality of care while simultaneously reducing the costs of providing it (Gawande, 2010).

Finally, our paper contributes to a recent literature specifically focused on the economics of the dialysis industry (e.g., Dai, 2014; Cutler et al., 2017; Dai and Tang, 2015; Grieco and McDevitt, 2017; Eliason, 2019; Gaynor et al., 2018; Wilson, 2016a,b). Within this literature, our paper is most closely related to Cutler et al. (2017), who study how market concentration in

[5]Eliason et al. (2018) hint at this by documenting how long-term acute care hospitals acquired by national chains change their discharge practices.

[6]See, for example, the finding in Dafny and Dranove (2009) that "up-coding" increases when independent hospitals become affiliated with for-profit chains.

the dialysis industry impacts quality and the price charged to privately insured patients. Using data from the Health Care Cost Institute and Dialysis Facility Compare (DFC), they exploit mergers of national dialysis chains as shifters in local market concentration and find no effect of concentration on quality and a weakly positive effect on prices. This differs substantially from our paper in a number of ways. First, they perform their analysis at an aggregate level because they do not observe patient-level data and are unable to match data from private insurers to facilities from DFC. By contrast, much of our analysis is performed at the patient level, allowing us to control for a large set of patient covariates and to observe how quality and treatment change within a facility — and even within a patient — over time. Moreover, our paper focuses on the role of a chain's strategy in treatment decisions, which is less likely to be influenced by local market competition. Also similar to our paper, Garg et al. (1999), Zhang et al. (2014), and Thamer et al. (2007) study the effect of facility ownership on patients' treatments. The first two of these papers provide descriptive evidence that for-profit facilities and chain-owned facilities, respectively, are less likely to refer patients to the transplant waitlist, with Garg et al. also finding lower mortality rates at for-profit facilities. Zhang et al. (2011) further show that chain-owned facilities have higher mortality rates than independent facilities, while Thamer et al. (2007) find that patients at non-profit dialysis facilities receive lower EPO doses than those at for-profit chain facilities. None of these papers, however, consider how acquisitions change firm strategies or the causal mechanisms through which they affect patient outcomes.

The rest of the paper proceeds as follows. Section 2 summarizes important institutional details of the dialysis industry. Section 3 describes our data. Section 4 presents our main results on the effects of dialysis facility acquisitions. Section 5 shows that these effects do not vary based on market concentration. Section 6 considers other explanations for why independent facilities behave differently than chains. Section 7 concludes. The appendices contain further details on the sample construction as well as analyses that, among other things, illustrate the robustness of our findings.

2 Background on the Dialysis Industry

2.1 Medical Background

The kidneys perform two primary functions in the human body: they filter wastes and toxins out of the blood and produce erythropoietin, a hormone that stimulates red blood cell production. The diagnosis for patients experiencing chronic kidney failure, where their kidneys no longer adequately perform these functions, is called end-stage renal disease (ESRD). To survive, ESRD patients must either receive a kidney transplant or undergo dialysis, a medical treatment that mechanically filters wastes and toxins from a patient's blood. Although a transplant is considered the best course of treatment, it is often not possible, either due to a lack of available kidneys or the patient's poor physical condition. Fewer than 20% of dialysis patients are currently on a kidney waitlist, and for those who are, the median wait time for a transplant is 3.6 years (United States Renal Data System, 2014). As a result, most patients with kidney failure rely on dialysis, either permanently or for an extended period.

Those with ESRD may receive one of two types of dialysis, hemodialysis or peritoneal dialysis. Hemodialysis uses a machine (also referred to as a station and designed to treat one patient at a time) to circulate blood through a filter outside the body, which can be performed at the patient's home or at a dialysis center, whereas peritoneal dialysis uses the lining of the patient's abdomen to filter blood inside the body.[7] Because over 90% of dialysis patients choose in-center hemodialysis, we focus on this modality for our analysis.

In addition to dialysis, most ESRD patients also receive treatment for anemia because they do not naturally produce enough erythropoeitin, which leads to a deficiency of red blood cells (Besarab et al., 1998). Anemia is treated with a cocktail of injectable drugs, most commonly an erythropoietin stimulating agent (ESA) known as Epogen (EPO), along with an intravenous iron analog, such as Venofer or Ferrlecit. Patients most commonly receive these drugs while being treated at a dialysis facility.

A dialysis facility's quality of care may be assessed from both clinical indicators and patient

[7]For more information, see `https://www.niddk.nih.gov`.

outcomes. Among the clinical measures, the two most prominent are the urea reduction ratio (URR) and hemoglobin (HGB) levels. The first, URR, measures the percent of primary waste (i.e., urea) filtered out of a patient's blood during dialysis, which increases as a patient spends more time on a machine. Although patients vary in how long it takes them to achieve a given URR, the standard of care is that a dialysis session should continue until a patient achieves a URR of at least 0.65 (Owen et al., 1993; NIH, 2009).

The second, a patient's HGB level, measures the onset or severity of anemia. During the period of our study, the FDA recommended that patients receive EPO doses that achieve HGB levels between 10 and 12 grams per deciliter (g/dL) (Manns and Tonelli, 2012). On the lower end, patients with HGB below 10g/dL are anemic and suffer from symptoms such as fatigue, weakness, dizziness, headaches, and, in some severe cases, death. On the other side of this range, high levels of HGB can result in serious complications, such as cardiovascular events (Besarab et al., 1998; Singh et al., 2006).

Along with these clinical measures, patient outcomes such as mortality and hospitalization represent additional indicators of a facility's quality of care. Of particular concern to dialysis patients and providers are hospitalizations for septicemia and cardiovascular events (Schrier and Wang, 2004). Septicemia, an infection of the blood for which dialysis patients are especially susceptible due to their weakened immune systems and frequent connection between the dialysis machine and their bloodstream, poses a severe risk for patients. Providers can reduce infections by properly cleaning machines between patients (Patel et al., 2013), but this is costly since it takes up to an hour to adequately sanitize a dialysis station (Grieco and McDevitt, 2017). Consequently, hospitalizations for septicemia reflect poor operational oversight by providers and impose heavy costs on patients and the health-care system. ESRD patients also face an elevated risk for cardiovascular events such as myocardial infarction and stroke, a risk made worse through excessive use of EPO (Besarab et al., 1998; Singh et al., 2006).

2.2 The Role of Medicare in Dialysis

A defining feature of the dialysis industry is that 90 days after being diagnosed with ESRD, all patients become eligible for Medicare coverage, regardless of age, which makes Medicare the primary payer for most ESRD patients. In 2014, over 80% of the 460,000 ESRD patients receiving dialysis treatments in the U.S. were enrolled in Medicare. As a result, Medicare spends more than $33 billion each year for costs associated with ESRD, approximately 1% of the entire federal budget (Ramanarayanan and Snyder, 2014).

Throughout the time period of our study, Medicare used a blended payment policy to reimburse dialysis providers. Specifically, Medicare paid a composite rate of around $128 per dialysis treatment, up to three times per week for each patient, with injectable drugs reimbursed separately on a fee-for-service basis. For these drugs, providers were reimbursed at a rate equal to 95% of their average wholesale price prior to 2005.[8] After investigations by the Centers for Medicare and Medicaid Services (CMS) found that providers were being reimbursed much more than they were spending, Congress altered the payment scheme to be 106% of the average sales price, a more accurate reflection of the drugs' true costs for providers. In both of these schemes, providers were reimbursed at a fixed rate for each administered unit, a crucial feature of the industry that we study below.

Prior to 2011, dialysis providers exploited fee-for-service injectable drugs as significant sources of revenue by strategically choosing both which drugs to use and how much to administer. In our analysis, we focus on the three most prevalent injectable anemia drugs: EPO, Venofer, and Ferrlecit. The first of these, EPO, is by far the most common, with more than 90% of dialysis patients receiving EPO in the mid 2000s and annual expenditures reaching $2 billion in 2010, making it the largest prescription drug expense for CMS (U.S. Government Accountability Office, 2012). Administering EPO proved lucrative for providers, accounting for as much as 25% of DaVita's revenue and up to 40% of its accounting profits (DaVita, 2005). Many patient advocates questioned such pervasive use of EPO, however, as several studies linked excessive EPO doses to an increased risk of mortality and cardiovascular events (Besarab et al., 1998;

[8] This was reduced to 85% in 2004.

Singh et al., 2006; Brookhart et al., 2010).

The other two anemia drugs, Ferrlecit and Venofer, are intravenous iron supplements used to treat iron-deficient anemia patients; they are essentially substitutable (Kosch et al., 2001) and both offered generous reimbursements. In 2007, total Medicare expenditures for these two drugs were $68 million and $166 million, respectively, making them the fourth and sixth most highly reimbursed drugs under Medicare Part B. Both are sold by their manufacturers in single-use vials, and any amount of the drug left over in a vial must be discarded to reduce the risk of infection, with CMS reimbursing facilities for the amount in the vial rather than the amount actually administered to the patient. Although Ferrlecit and Venofer had nearly identical per-milligram reimbursement rates during our study period, Venofer was produced exclusively in 100mg vials, while Ferrlecit was produced in 62.5mg vials. As a result, facilities could effectively receive higher reimbursements per vial for Venofer because they could, for example, use 25mg from four vials rather than one 100mg vial but still bill CMS for four 100mg vials, discarding 75mg from each of the four (i.e., under this scheme they could bill for 400mg of Venofer as opposed to 250mg of Ferrlecit). One company accused of engaging in this practice paid $450 million to settle a whistleblower lawsuit (Pollack, 2011; Stempel, 2015).

Beginning in 2011, Medicare made a number of changes to the way it reimburses dialysis providers. In particular, it substantially changed its reimbursement policy by bundling dialysis and anemia treatment (including injectable drugs) into a single prospective payment, changing the case-mix adjustments to those payments, and introducing the Quality Incentive Program. Because these reforms likely had many confounding effects on the dialysis industry, in this paper we restrict our analysis of facility acquisitions to the years spanning 1998 to 2010 and study the effects of the 2011 reform in a separate paper (Eliason et al., 2019b).

Although Medicare covers the vast majority of dialysis patients in the U.S., those who have private insurance and become eligible for Medicare solely due to ESRD retain that coverage for the first 30 months of treatment before Medicare becomes the primary payer.[9] Reimbursements from private insurers tend to be much higher than those from Medicare, with estimates suggesting

[9]Including the 90-day waiting period for Medicare eligibility, private insurance coverage may last up to 33 months.

that the average private insurance rates are anywhere from 2.1 times (United States Renal Data System, 2013) to 4.5 times (Boyd, 2017) as generous as Medicare.[10]

2.3 The Market for Dialysis

Dialysis patients choose their provider much like they do in other segments of the U.S. health-care system, with those covered under Medicare able to receive treatment at any facility that has an opening for them. Patients primarily receive dialysis at one of the more than 6,000 dedicated dialysis facilities across the country, where they typically go three times per week for treatment that lasts 3-4 hours each visit.[11] These facilities are run by a mix of for-profit and non-profit firms, and over the past three decades the two largest for-profit chains, DaVita and Fresenius, have grown to the point where they now control over 60% of facilities and earn 90% of the industry's revenue (United States Renal Data System, 2014; Baker, 2019). The remainder of the market comprises smaller chains as well as independent facilities that are often run by nephrologists.

Dialysis chains potentially have a number of advantages over independent facilities. Large chains, for example, may have lower average costs due to volume discounts for pharmaceuticals as well as centralized clinical laboratories; they may have a stronger bargaining position with commercial insurance companies (Pozniak et al., 2010); and their national brand and network may make them more attractive to patients.

Chains also stand apart from independent facilities by having firm-wide standards that they implement across their facilities. Notably, large chains have operation manuals that dictate each of their facilities' procedures during treatment. We see evidence of this standardization in the predictability of a patient's EPO dose: an acquired facility's use of EPO becomes nearly twice as predictable — and twice as high — compared to its pre-acquisition doses.[12] The use of these

[10] According to DaVita's 2007, 10-K the average patient with private insurance generated 3.8 times more revenue than the average Medicare patient.

[11] Unless otherwise specified, for the rest of the paper when we use the term "dialysis" we are referring to in-center hemodialysis.

[12] These statements about predictability are based on comparing R^2 from regressions of EPO dose per patient on patient characteristics interacted with year fixed effects estimated separately using observations from facilities that are acquired either pre- or post-acquisition. See results in Appendix I.

manuals represents a clear channel through which an acquisition could alter patients' treatments and outcomes, which we study at length below.

Chains' system-wide standards do not universally lead to higher-quality care, however, as anecdotal evidence presented by the media, as well as some governmental reports, have raised concerns about practices and outcomes at both independent and chain facilities. For example, an investigative journalist from ProPublica examined the inspection records of more than 1,000 facilities and found that surveyors came across filthy or unsafe conditions in almost half the units they checked (Fields, 2010).[13] Similarly, *The New York Times* and *Washington Post* have both reported on the excessive use of injectable drugs at dialysis facilities, noting that despite the billions spent on anemia drugs, there is little evidence that they improve patients' quality of life (Berenson and Pollack, 2007; Whoriskey, 2012). Multiple reports by the Office of the Inspector General have also scrutinized dialysis facilities' drug use and acquisitions.[14] In addition to bad press, extreme cases of poor conditions and treatment quality have led to a number of lawsuits against providers.[15]

Moreover, the media has reported claims that chains potentially provide worse care by discouraging their patients from seeking kidney transplants (Matthews, 2017; Oliver, 2017). Although patients can self-refer for a transplant, they often lack adequate information about the procedure and fail to understand its risks and benefits. Facilities thus play an important role in a patient's decision to pursue a transplant, and some have allegedly discouraged patients from seeking one out to avoid losing their reimbursements (OPTN Minority Affairs Committee, 2015). In the analysis below, we will move beyond such anecdotes and use our comprehensive claims data to directly consider the transference of firm strategy via acquisition and its impact on patient outcomes.

[13]At some facilities, blood was found encrusted on patients' treatment chairs or even splattered around the room. At a unit in Durham, N.C., ants were reportedly so common that staffers would simply hand a can of bug spray to patients who complained.

[14]See OEI-03-06-00200 or OEI-03-06-00590 for two examples.

[15]As an example, in 2008 Fresenius Medical Care North America agreed to settle a wrongful-death lawsuit brought by a deceased patient's survivors. According to a federal inspection report, during treatment the patient's bloodline became disconnected and, contrary to emergency standing orders, the dialysis technician reconnected the line to the patient's catheter, "infusing him with 'potentially contaminated blood'." He was later taken to a hospital where tests showed that his catheter had become infected with antibiotic-resistant staph. The infection moved to his heart and brain and he died a few days later.

3 Data and Descriptive Statistics

A primary contribution of our paper is to show how acquisitions affect the quality of care provided by dialysis facilities, which we accomplish in part by tracking patients' treatments and tests before and after their facilities are acquired. The micro-level data we use in our analysis are essential for observing any changes in a facility's strategic choices and how these choices subsequently impact patients' outcomes and overall Medicare spending. In this section, we describe our data and provide descriptive results for the most-prominent changes in firm strategy.

3.1 Data Sets

For our analysis, we use patient- and facility-level data from the United States Renal Data System (USRDS). The USRDS is a data clearing house funded by the National Institute of Diabetes and Digestive and Kidney Diseases and the National Institute of Health that collects and stores data related to chronic kidney disease. They combine data from a variety of sources, including Medicare administrative files, Medicare claims, annual facility surveys, and clinical surveillance data, to create the most-comprehensive data set for studying the U.S. dialysis industry.[16] Appendix H provides further details on how we constructed our sample.

Patient Data

USRDS uses a number of data sources to create an exhaustive treatment history for almost all dialysis patients in the U.S. since at least 1991. Patients' demographic information is obtained from the Medical Evidence form submitted to Medicare by providers at the patient's onset of ESRD, which CMS uses to determine eligibility for Medicare coverage.[17] Information collected at this time includes a patient's sex, race, BMI, cause of ESRD, payer, hemoglobin levels, measures of kidney failure, comorbidities (e.g., diabetes and hypertension), type of initial treatment, residential ZIP Code, and facility. After initiation, a patient's residence is updated over time in

[16] For a more thorough description of USRDS, see the *Researcher's Guide to the USRDS System* at USRDS.org.

[17] The Medical Evidence form is used to establish the 90 day Medicare eligibility cutoff as well as the 30 month private insurance coordinating period. Consequently, it is required for all patients, regardless of payer.

the CMS Medicare Enrollment Database.

Using a number of different sources, USRDS constructs the Treatment History Standard Analytical File (SAF), which details the complete ESRD treatment history for all patients included in the USRDS database. These data come primarily from the Consolidated Renal Operations in a Web-Enabled Network data system (CROWNWeb), a system established by CMS to track the treatment of ESRD patients. This system contains information submitted by the provider regarding treatments for each individual patient over the previous month.

We combine these data with institutional claims from Medicare, which provide a more granular view of the dialysis treatments received by Medicare patients. Providers submit line-item claims for services other than dialysis. These include all the injectable drugs administered during treatment, which we identify by their Healthcare Common Procedure Coding System (HCPCS) codes.[18] Unique to this setting, the claims also include clinical measures related to dialysis care and anemia treatment at a monthly frequency, making them among the more-detailed claims data available to researchers.

Transplant and waitlisting events are available to us through the Transplant and Transplant Waiting List SAFs. The Transplant File includes a patient and provider ID for each kidney transplant received by a patient in the USRDS database. Similarly, the Transplant Waiting List SAF includes information on a patient's waitlist status, including their listing date and the transplant center where they are waitlisted.[19] Both of these files are populated using information from the Organ Procurement and Transplantation Network operated by the Department of Health and Human Services.

We focus primarily on four patient outcomes: mortality, hospitalization, urea reduction ratios, and hemoglobin levels. Mortality information comes from the USRDS Patient History File, which includes a date of death for patients. USRDS constructs this variable using information from the CMS Death Notification form, CROWNWeb, and the Social Security Death Master File.

[18] We use all HCPCS codes for epoeitin alfa, ferric gluconate, and iron sucrose according to the CMS pricing guide at `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Part-B-Drugs/McrPartBDrugAvgSalesPrice/`.

[19] A patient is waitlisted at a particular transplantation center. They are able to be listed at multiple centers concurrently.

Hospitalization data come from institutional claims obtained from Medicare. We focus on three categories of hospitalizations, classified by their reported diagnoses: all cause, septicemia, and cardiovascular events. Urea reduction ratios and hemoglobin levels are reported in the claims data. Medicare required facilities to report urea reduction ratios for all dialysis claims and hemoglobin levels for ESA claims during our sample period, and for all dialysis claims since 2008.[20] With the exception of mortality, we only observe these outcomes for patients for whom we have claims data.

Facility Data

Dialysis facilities must be certified by CMS to receive reimbursements for ESRD treatment, with the CMS ESRD Annual Facility Survey administered each year to all certified facilities. It records information including the facility ID, address, chain affiliation, labor inputs, number of dialysis stations, for-profit status, and types of treatment offered (e.g., hemodialysis, peritoneal dialysis, or transplant). Using these data, we construct a yearly panel of chain ownership for each facility in our sample. This allows us to examine, at a yearly level, how changes in ownership affect the treatment received by patients.

To construct a monthly panel of chain ownership, we first find all facility-years in our yearly facility panel where the facility listed no chain ownership in one year but did so the following year. We then obtain precise acquisition dates for each facility using data from the Provider of Services (PoS) data set and annual cost reports submitted to CMS, each of which lists certification and change of ownership dates. From this algorithm, we are able to find precise acquisition dates for 1,055 of the 1,236 acquisitions we observe.[21]

In addition to the Annual Facility Survey, providers are required each year to submit certified financial statements to CMS detailing their costs of providing care as part of the Healthcare Cost Reporting Information System (HCRIS), which CMS reserves the right to audit. We use these reports to construct measures of per-unit EPO costs and per-treatment variable costs.

[20] Prior to 2008, hemoglobin measures are missing for patients who were not treated with ESAs. But because more than 97% of patients received ESAs during this time period, we still have hemoglobin data for virtually all of our sample.

[21] A more-detailed description of this matching process is available in Appendix H.

We combine these data sets and drop any patient who is missing demographic or comorbidity data. We also drop observations at facilities that are acquired but do not have reliable dates of acquisition, as well as the 12-month window surrounding an acquisition to reduce measurement error in the timing of acquisition.[22]

3.2 Descriptive Statistics

Figures 1-3 illustrate the significant change in the dialysis industry's market structure over our sample period. Figure 1 shows that the number of acquisitions has varied between 50 to 150 each year, and by 2010 we observe over 1,200 first-time acquisitions of independent facilities, providing us a large sample to conduct our analysis.

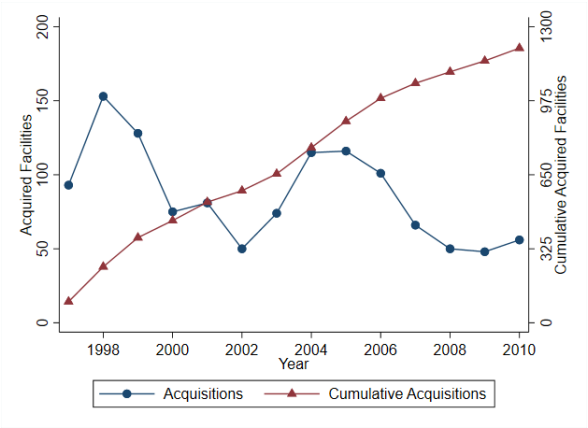


Figure 1: Acquisitions of Independent Dialysis Facilities, 1998-2010

Consolidation increased sharply during our sample period. Figure 2 illustrates the extent of this change, with DaVita and Fresenius owning the majority of facilities by 2010 and the other chains collectively commanding a somewhat smaller market share. The two biggest mergers during this time period are DaVita and Fresenius' acquisitions of the large chains Gambro and Renal Care Group, respectively. As opposed to these large mergers, we focus instead on the acquisition of independent facilities, as they allow us to cleanly link changes in ownership to the resulting changes in behavior and outcomes. Figure 3 illustrates how the acquisitions of

[22]Our qualitative results are robust to the inclusion of this time period, though quantitative results are somewhat attenuated due to the introduction of measurement error in the timing of acquisitions. See Appendix B.

independent facilities have contributed to each chain's overall growth during our sample period.[23]

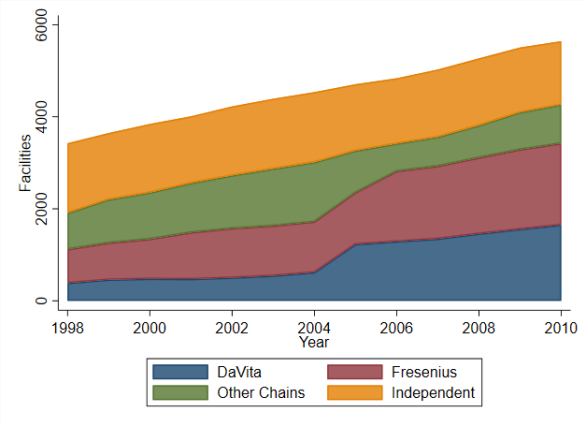


Figure 2: Dialysis Market Evolution, 1998-2010

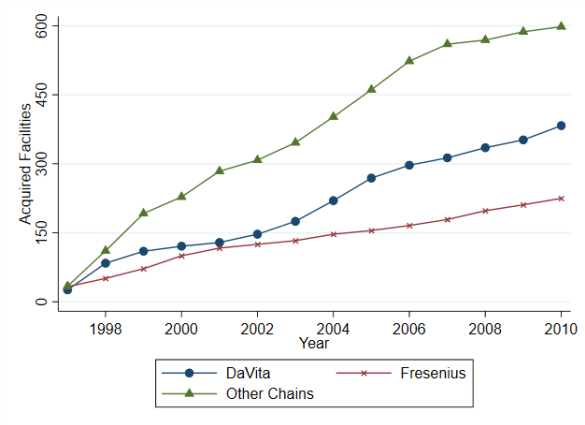


Figure 3: Dialysis Facility Acquisitions by Major Chains Over Time, 1998-2010

[23] As Wollmann (2018) points out, one reason why such consolidation is possible is that most of the acquisitions that led to these firms' growth were exempt from the Hart-Scott-Rodino's pre-merger notification program due to the relatively small size of the target firms.

Table 1 presents descriptive statistics at a patient-month level for all of the covariates included as controls in our analysis. The first set of covariates includes clinical characteristics. In addition to comorbid conditions, our data include important blood chemical tests that indicate the severity of each patient's kidney failure, such as the glomerular filtration rate (GFR) that measures residual kidney function. Specifically, it measures how much blood passes through the glomeruli, tiny filters in the kidneys, each minute, with a GFR below 15 possibly indicating kidney failure (Stevens et al., 2006). Levels of albumin, a protein found in blood that contributes to the health of red blood cells and facilitates the dialysis filtration process, also reflect the health of a patient's kidneys, with albumin levels below 3.0g/dL associated with increased hospitalizations and risk of mortality (Owen et al., 1993).

Of the comorbid conditions, cardiovascular conditions (the last four conditions in the Clinical Characteristics panel) are widespread among dialysis patients. In total, approximately 50% of patients have at least one cardiovascular condition, with congestive heart failure the most common. The prevalence of such conditions makes any increase in EPO doses especially hazardous due to the concern that it elevates a patient's risk of cardiovascular events (Besarab et al., 1998; Singh et al., 2006). Dialysis patients are also disproportionately African-American, comprising over 30% of our sample compared to less than 15% of the U.S. population. In our analysis, we also include demographic characteristics that vary both across ZIP Codes and within a ZIP Code over time. Lastly, in our regressions we control for the age of the facility and, in specifications without facility fixed effects, the facility's elevation, as medical evidence suggests that elevation influences a patient's need for EPO.[24]

Table 2 presents descriptive statistics at a patient-month level, split by acquisition status, to investigate the potential identification challenges that we must address with our empirical strategy. Namely, patients at acquired facilities may be inherently different from patients at facilities that are not acquired, and the patient mix at acquired facilities could change after an

[24]At higher elevations, the richness of oxygen in the blood decreases and tissue-hypoxia sets in, which causes the body to produce more endogenous erythropoietin (Brookhart et al., 2011). Although ESRD patients still require exogenous erythropoietin in the form of ESAs, the more-efficient use of erythropoietin at higher elevations results in correspondingly lower required dosages of EPO. Eliason et al. (2019b) exploit this feature of anemia treatment to study the effect of the 2011 dialysis payment reforms on patient and market outcomes.

Table 1: Patient, Area, and Facility Covariate Descriptive Statistics

	Mean	Std. Dev.
Clinical Characteristics		
Diabetic (%)	54.66	(49.78)
Hypertensive (%)	85.11	(35.60)
BMI	28.32	(7.72)
GFR	7.79	(4.55)
Albumin $\geq$ 3.0g/dL (%)	52.22	(49.95)
Hemoglobin	7.62	(2.98)
Cancer (%)	4.78	(21.32)
Drug Use (%)	1.14	(10.60)
Alcohol Use (%)	1.38	(11.67)
Smoker (%)	5.65	(23.08)
Requires Assistance (%)	4.99	(21.78)
Chronic Obstructive Pulmonary Disease (%)	6.30	(24.29)
Atherosclerotic Heart Disease (%)	5.22	(22.24)
Peripheral Vascular Disease (%)	12.32	(32.86)
Ischemic Heart Disease (%)	15.33	(36.03)
Congestive Heart Failure (%)	29.68	(45.68)
Patient Demographics		
Male (%)	52.72	(49.93)
Non-Hispanic White (%)	44.00	(49.64)
Black (%)	36.92	(48.26)
Hispanic (%)	13.79	(34.48)
Asian (%)	2.65	(16.05)
Other Race (%)	4.88	(21.55)
Age (Years)	63.78	(14.91)
Months With ESRD	36.16	(30.46)
Distance (Mi.)[a]	5.03	(116.83)
Area Demographics		
% High School	32.75	(10.09)
% College	8.00	(8.02)
Median Income ($)	48,232.59	(19,279.56)
Facility Characteristics		
Facility Age (Years)	13.19	(8.70)
Facility Elevation (ft.)	196.43	(282.63)
Patient-Months	14,161,244	

Notes: See text for more detail.
[a] Median distance is displayed instead of mean.

acquisition. The top panel shows how the different types of facilities vary by demographics, while the middle panel shows how they vary by clinical characteristics. For many of these attributes, we observe no systematic differences across facility-types, such as age, BMI, GFR, and congestive heart disease. We also see no meaningful difference in the share of privately insured patients across each type of facility. We do observe differences in racial composition and the rates of ischemic heart disease, however, with these differences largely coming from long-run trends in patient characteristics, as the pre-acquisition column tends to sample from earlier years and the post-acquisition column from later years. For example, the prevalence of ischemic heart disease among dialysis patients has declined from 21.8% in 1998 to 10.6% in 2010. Reflecting this, when we consider only those patients treated within 12 months of the acquisition window, we find no meaningful difference between the pre- and post-acquisition groups (see Appendix A). This further suggests that any meaningful differences in demographics are driven by time trends, not changes in the mix of patients treated at facilities following an acquisition.

Nevertheless, in the analysis that follows, we directly consider the possibility that an acquisition may affect the mix of patients in ways that could bias our results. To ensure that time trends and selection bias do not confound our analysis, we control for detailed patient characteristics and include month-year fixed effects in our regressions. To further address any concerns that our findings may be driven by changes in patient unobservables, we show that our results are robust to including patient fixed effects in Appendix C. Additionally, in Section 4.4 we present evidence that patients starting dialysis at acquired facilities may be healthier than those beginning treatment at the same facility before acquisition, suggesting that the deterioration in outcomes we estimate may actually be understating the true decline.

These descriptive statistics also highlight stark differences in the treatments received by patients at each type of facility. As the top panel of Table 2 clearly shows, patients at chain-owned facilities receive substantially more EPO per session and are much more likely to receive Venofer than Ferrlecit. As a result, payments per session (all Medicare payments to the dialysis facility including injectable drugs per session) jump by about 7% at facilities acquired by a chain.

Treatments are not the only dimension along which we see changes in firm strategy following

Table 2: Patient and Treatment Descriptive Statistics by Facility Type

	Always Independent	Pre-Acquisition	Post-Acquisition	Always Chain
Treatment				
EPO Per Session ('000 IU's)	4,495.66	4,728.87	6,223.04	6,259.82
Venofer Per Session (mg)	7.95	7.60	15.93	14.86
Ferrlecit Per Session (mg)	6.49	7.22	4.65	4.86
Payments Per Session	179.22	171.79	184.58	183.15
Waitlist or Transplant[a] (%)	10.92	9.63	9.76	9.52
Clinical Characteristics				
Diabetic (%)	53.72	54.32	55.38	54.90
Hypertensive (%)	84.34	84.56	85.85	85.32
BMI	28.16	27.92	28.63	28.38
GFR	7.92	7.74	7.99	7.71
Albumin $\geq$ 3.0g/dL (%)	54.50	52.53	53.59	50.99
Hemoglobin	7.68	7.67	7.73	7.56
Cancer (%)	5.18	5.59	4.91	4.44
Drug Use (%)	1.22	1.13	0.98	1.15
Alcohol Use (%)	1.48	1.31	1.20	1.40
Smoker (%)	5.27	6.35	5.80	5.62
Requires Assistance (%)	5.85	4.46	4.88	4.81
Chronic Obstructive Pulmonary Disease (%)	6.79	7.59	6.66	5.78
Atherosclerotic Heart Disease (%)	5.74	7.18	4.76	4.77
Peripheral Vascular Disease (%)	13.44	14.33	12.53	11.47
Ischemic Heart Disease (%)	17.25	20.58	14.84	13.75
Congestive Heart Failure (%)	31.07	32.04	30.29	28.56
Demographics				
Male (%)	53.87	53.18	52.93	52.15
Non-Hispanic White (%)	48.56	53.42	44.41	40.44
Black (%)	32.30	30.65	36.23	39.98
Hispanic (%)	13.06	10.03	13.79	14.77
Asian (%)	3.33	2.57	2.62	2.41
Other Race (%)	5.61	5.33	4.91	4.52
Age (Years)	64.31	64.53	64.02	63.38
Months With ESRD	35.83	31.75	37.06	36.88
Distance (Mi.)[b]	4.93	5.36	5.11	5.00
Area Demographics				
% High School	31.79	33.24	33.19	32.90
% College	9.10	7.81	7.46	7.76
Median Income ($)	50,404.87	48,202.46	47,441.34	47,637.76
Facility Characteristics				
Facility Age (Years)	14.08	12.02	10.10	13.86
Facility Elevation (ft.)	195.54	198.65	211.42	192.58
For-Profit (%)	40.99	64.09	96.40	88.70
Patient-Months	2,880,503	1,483,917	1,960,286	7,836,538
Incident Patients	235,144	142,815	126,582	400,161

Notes: See text for more detail.

[a] Dummy variable for being waitlisted or transplanted within 1 year for incident patients only.

[b] Median distance is displayed instead of mean.

Table 3: Facility Summary Statistics

	Always Independent	Pre-Acquisition	Post-Acquisition	Always Chain
Stations	14.30	16.63	18.39	17.92
	(8.63)	(7.82)	(8.13)	(7.39)
Hemodialysis (%)	89.90	91.69	92.36	94.22
	(19.25)	(15.92)	(14.76)	(13.06)
Privately Insured (%)	6.52	7.43	6.66	6.79
	(6.17)	(5.85)	(4.12)	(5.38)
Nurses	5.61	5.14	4.23	3.70
	(4.06)	(3.76)	(2.63)	(2.26)
Technicians	4.95	6.20	6.65	6.22
	(5.09)	(4.77)	(4.53)	(4.12)
Nurses/Techs	1.62	1.08	0.77	0.72
	(2.21)	(1.17)	(0.70)	(0.59)
Patients/Employee	4.14	4.75	5.84	5.52
	(2.76)	(2.14)	(2.09)	(2.34)
Has Night Shift (%)	24.85	23.85	23.88	18.47
	(43.22)	(42.62)	(42.64)	(38.81)
For-Profit (%)	35.15	66.48	94.12	88.10
	(47.75)	(47.21)	(23.53)	(32.37)
Facility Elevation (ft.)	251.24	205.88	209.83	229.52
	(359.41)	(242.46)	(282.05)	(342.04)
Facility Age (Years)	12.93	9.11	9.74	10.98
	(9.71)	(8.61)	(7.11)	(8.50)
Facility-Years	7,824	4,063	4,137	16,459

Notes: An observation is a facility-year. Standard deviations are in parentheses.

an acquisition. Table 3 shows that chain-owned facilities have more stations per facility, substitute towards lower-cost technicians and away from higher-cost nurses, and generally stretch resources further by treating more patients per employee. All of these differences are consistent with a firm strategy that prioritizes profits over patient outcomes, which we consider in greater detail in the next section.

4 The Impact of Acquisitions on Firm Strategy, Patient Outcomes, and the Cost of Dialysis Care

In this section, we show how independent facilities change their behavior after being acquired by a chain and how these changes then impact the quality and cost of care. To do so, we use a difference-in-differences research design that compares independent facilities acquired by chains to those that are never acquired:

$$Y_{ijt} = \beta^{Pre} D_{jt}^{Pre} + \beta^{Post} D_{jt}^{Post} + \beta^{Chain} D_{jt}^{Chain} + \alpha X_{ijt} + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is the outcome of interest for patient i at facility j in month t; D_{jt}^{Pre} and D_{jt}^{Post} are indicators for whether facility j in month t will be acquired in the future or has already been acquired; and D_{jt}^{Chain} is an indicator for whether facility j is always owned by a chain. The excluded category comprises independent facilities that are not acquired during our sample period. Although X_{ijt} varies by specification, in our preferred specification it includes a host of facility and patient controls, including age, comorbidities, race, sex, time on dialysis, and facility age; X also includes year, state, and facility fixed effects. Without facility fixed effects, β^{Post} would capture the mean difference in Y for facilities that have been acquired relative to facilities that are never acquired in our sample, conditional on other covariates. To avoid measurement error in our determination of the exact date of acquisition, and to allow enough time for a firm's strategy to be fully implemented at an acquired facility, we exclude all observations within a six-month window on either side of the acquisition date. As shown in Appendix B, however, our main results are robust to including this period, although slightly attenuated due to the introduction of measurement error in the timing of acquisitions. In all specifications, we cluster standard errors at the facility level.[25]

The primary threat to identification in this setting is that chains may acquire independent facilities whose patients have certain characteristics that affect Y through channels other than a change in ownership. As shown in Table 2, however, patients treated at independent facilities

[25] Clustering at the patient level yields standard errors 25-75% smaller than those clustered at the facility level, so we report standard errors clustered by facility as the more conservative of the two approaches.

acquired by chains are not systematically different along observable characteristics than those treated at other independent facilities. Additionally, the richness of our data allows us to control for all clinically relevant covariates, making this an even smaller concern. Lastly, to make a causal claim about acquisitions from a specification that includes facility fixed effects requires only that chains do not systematically *change* the mix of patients along *unobservable* dimensions when they acquire a facility, a relatively weak assumption. Moreover, our results are robust to the inclusion of patient fixed effects, which further limits this concern. Nevertheless, in Section 4.4 we also explore the possibility that patient selection may be a part of the strategy chains implement post acquisition and find that new patients at acquired facilities may be slightly healthier than those who were at the same facilities before they were acquired. These findings, if anything, suggest that our results may understate the true effects of an acquisition. In short, the rich data of our empirical setting allow us to cleanly identify the effects of acquisitions on facilities' practices and patients' outcomes, affording us a unique opportunity to disentangle the otherwise opaque nature and effects of firms' corporate strategies.

4.1 Drug Doses

We first consider the use of EPO at dialysis facilities due to its importance for firms' profits, its outsize effect on Medicare's total spending on drugs, and its potential for abuse by providers. Table 4 presents estimates of equation (1) where the dependent variable is the log of EPO doses per treatment.[26] Columns (1) and (2) of the table show that, although acquired facilities were already using slightly more EPO per treatment than independent facilities that are never acquired, they experience such a substantial increase following an acquisition that their levels converge to those of facilities always owned by a chain. Column (3) adds facility fixed effects but no patient or facility controls, while column (4) includes patient controls, facility fixed effects, and time-varying characteristics (e.g., facility age). The estimates in column (4) suggest that acquisitions cause EPO doses to more than double for patients at the same facility with the same observable characteristics.

[26]Dependent variable is log(1+Dose) in cases where the dose is 0.

Table 4: Effect of Acquisition on Per-Treatment EPO Doses

	(1) Epogen	(2) Epogen	(3) Epogen	(4) Epogen
Pre-Acquisition	0.265*	0.270*		
	(0.134)	(0.124)		
Post-Acquisition	1.485***	1.350***	0.781***	0.829***
	(0.0868)	(0.0822)	(0.0577)	(0.0725)
Always Chain	1.509***	1.343***		
	(0.0841)	(0.0775)		
Observations	14,161,244	14,161,244	14,161,244	14,161,244
Dep. Var. Mean	7.538	7.538	7.538	7.538
Units	log(IU)	log(IU)	log(IU)	log(IU)
Year x Month FE	X	X	X	X
Pat. & Fac. Controls		X		X
Facility FE			X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

To interpret this estimate as the causal effect of an acquisition on EPO doses, we are relying on the assumption that an acquisition creates a discontinuous change in facility behavior and that any trends in dosing during the period surrounding an acquisition are common to all of the facilities in the control group. To support this assumption, in Figure 4 we plot EPO doses during the time period around acquisition, where the horizontal axis has the quarters relative to acquisition, quarter 0 is the quarter of acquisition denoted by a vertical dashed line, and the omitted category is the quarter prior to acquisition. The graph plots coefficients from estimating

$$Y_{ijt} = \sum_s \delta^s D^s_{jt} + \alpha X_{ijt} + \epsilon_{ijt}, \tag{2}$$

where D^s_{jt} is a dummy variable for facility j being acquired at time $t+s$ and X_{ijt} includes the same set of controls as equation (1), including facility fixed effects. We find no evidence of a pre-trend.

We do see a short adjustment period of approximately 6 months following acquisition where facilities gradually adjust EPO doses upwards before leveling off. For this phenomenon to arise due to selection bias (in the sense that chains acquire facilities that were going to increase EPO doses irrespective of being acquired), acquiring firms would need to observe some indication of a looming increase in doses when negotiating the sale of the facility. This strikes us as implausible given that negotiations occur many months prior to the date of acquisition.

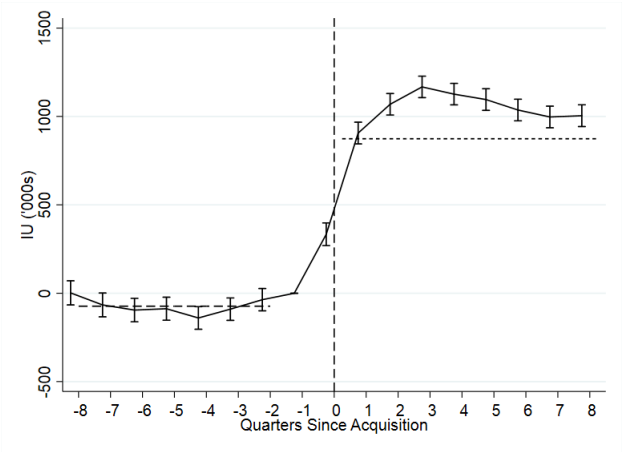


Figure 4: EPO Dosing Dynamics at Acquired Firms

Notes: Months outside the 48 month window are included in the regression but not shown here. Observations are binned by quarter to reduce noise. Error bars are 95 percent confidence intervals. Observations within 6 months of acquisition are included in this plot.

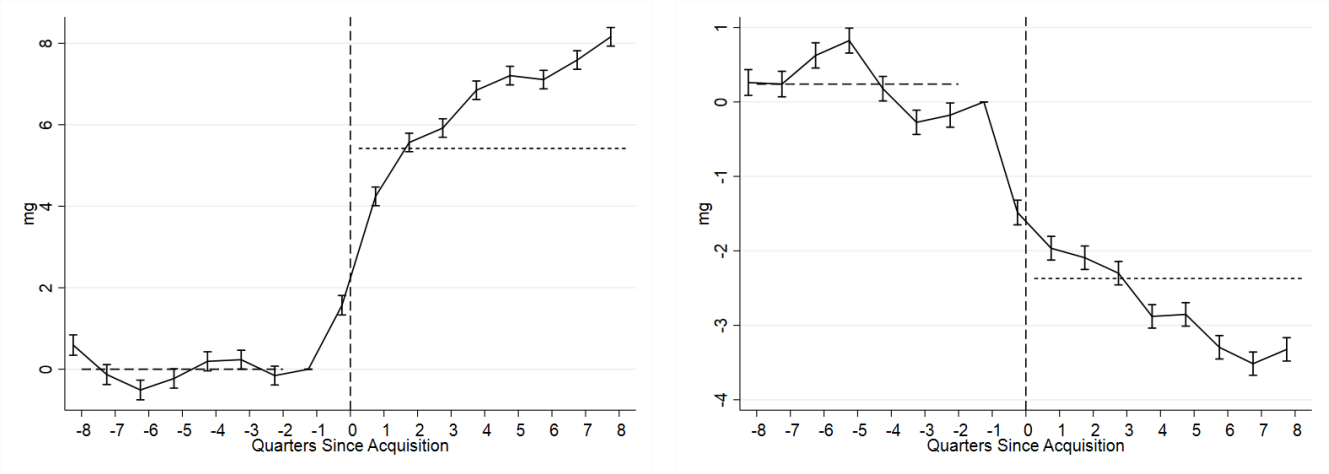
We extend our baseline analysis to study the effect of acquisitions on the use of two other commonly used intravenous drugs given to patients with anemia, the iron-supplement drugs Ferrlecit and Venofer. Table 5 repeats the research design used in Table 4 to focus on these drugs, with the number of observations differing across the columns because Ferrlecit and Venofer did not receive FDA approval until 1999 and 2000, respectively, whereas EPO was in use at the start of our sample in 1998. Due to delays in the creation of HCPCS codes, we have Ferrlecit doses since 2001 and Venofer doses since 2002. The results in Table 5 show that acquired facilities substantially increase their use of Venofer and decrease their use of Ferrlecit.

Table 5: Acquisition Effects on Drug Doses

	(1) Ferrlecit	(2) Ferrlecit	(3) Ferrlecit	(4) Ferrlecit	(5) Venofer	(6) Venofer	(7) Venofer	(8) Venofer
Pre-Acquisition	0.0126	-0.0188			0.0851	0.0650		
	(0.0561)	(0.0558)			(0.0591)	(0.0604)		
Post-Acquisition	-0.224***	-0.351***	-0.272***	-0.303***	0.720***	0.784***	0.582***	0.612***
	(0.0455)	(0.0466)	(0.0625)	(0.0627)	(0.0518)	(0.0555)	(0.0727)	(0.0751)
Always Chain	-0.209***	-0.335***			0.625***	0.722***		
	(0.0390)	(0.0391)			(0.0404)	(0.0454)		
Observations	12,473,162	12,473,162	12,473,162	12,473,162	11,595,400	11,595,400	11,595,400	11,595,400
Dep. Var. Mean	0.589	0.589	0.589	0.589	1.337	1.337	1.337	1.337
Units	log(mg)	log(mg)	log(mg)	log(mg)	log(mg)	log(mg)	log(mg)	log(mg)
Year x Month FE	X	X	X	X	X	X	X	X
Pat. & Fac. Controls		X		X		X		X
Facility FE			X	X			X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Venofer and Ferrlecit specifications have different observations due to the availability of the two drugs. Ferrlecit was introduced in 1999 and Venofer in late 2000. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

The switch from Ferrlecit to Venofer reflects the profits at stake. As discussed in Section 2.2, Ferrlecit and Venofer are essentially substitutes for one another and are reimbursed by Medicare at nearly the same per-unit rate, but differences in how manufacturers package the two drugs make Venofer a potentially more lucrative drug for providers because it allows them to bill for more "unavoidable" waste. To illustrate the onset of these strategies at newly acquired firms, we replicate Figure 4 for both Venofer and Ferrlecit in Figures 5a and 5b.[27]



(a) Venofer (b) Ferrlecit

Notes: Months outside the 48 month window are included in the regression but not shown here. Observations are binned by quarter to reduce noise. Error bars are 95 percent confidence intervals. Observations within 6 months of acquisition are included in this plot.

Figure 5: Venofer and Ferrlecit Dosing Dynamics at Acquired Firms

4.2 Facility Inputs

The results in Section 4.1 clearly show that chains strategically alter the drug doses of patients at newly acquired facilities. In this subsection, we investigate how they alter the input choices of their targets following takeovers in ways that reduce costs. To do so, we modify our baseline specification (1) to analyze data at the facility-year level, as data for many of the inputs (e.g., staff and the number of dialysis stations) are only available annually. Specifically, we include

[27]Event studies for the other variables shown in Sections 4.2 and 4.3 are available in Appendix G. We omit them from the body of the text for narrative clarity.

facility fixed effects and estimate specifications of the form

$$Y_{ijt} = \gamma^{Post} D_{jt}^{Post} + \delta X_{jt} + \nu_{jt}. \tag{3}$$

Aside from the change in the unit of observation, this analysis is very similar to our patient-level analysis and relies on similar identifying assumptions. Namely, for a causal interpretation of γ^{Post}, we require that the acquisition results in a discrete change in the environment determining facilities' input choices. With annual data, measurement error for the timing of acquisitions is an even greater concern because some inputs (e.g., staff) may change part way though the year, but we would not observe the new levels until the following year's report. To remedy this, we drop the entire year of acquisition for each facility that changes ownership, keeping only observations where a facility has the same ownership for the entire year.

Table 6 displays the effect of acquisitions on facility-level labor and capital decisions. These estimates show a consistent shift in the use of certain inputs by chains, with acquired facilities decreasing their use of nurses while increasing their use of dialysis technicians. Such a switch reduces facilities' costs because technicians have less training and are therefore paid much less than nurses.[28] Upon acquisition, the target firm decreases its nurse-technician ratio by roughly 15.1%. Newly acquired facilities also stretch their resources by increasing their patient-to-employee ratio by 11.7% and their patient-to-station ratio by 4.5%. Taken together, we find that acquiring firms adjust the inputs of their targets by substituting away from more-experienced, higher-cost labor and by increasing both the number of patients per employee and station.

Although these changes reduce the acquired facilities' operating costs, patients may have worse outcomes if being treated by busier employees with less training diminishes their quality of care. Moreover, if the number of patients per station increases because the time each patient spends on a machine decreases, or because machines are not adequately cleaned between patients, this, too, may result in worse outcomes for patients, as shown in Grieco and McDevitt (2017). In the next section, we will show that these changes in firm strategy following an acquisition

[28]Dialysis technicians typically require only 12 months of training, much of which is done on the job. By contrast, nurses are typically required to pass an RN licensure exam.

directly impact the quality and cost of patient care.

Table 6: Acquisition Effects on Facility Input Choices

	(1) Nurses	(2) Technicians	(3) HD Patients	(4) Total Stations	(5) Nurses per Tech	(6) Patients per Employee	(7) Patients per Station	(8) Employees per Station
Post-Acquisition	-0.0204	0.0456*	0.134***	0.0210	-0.146***	0.599***	0.179*	-0.0289
	(0.0194)	(0.0230)	(0.0187)	(0.0410)	(0.0410)	(0.107)	(0.0825)	(0.0185)
Observations	24,868	24,868	42,944	43,046	23,217	24,868	43,046	24,868
Dep. Var. Mean	1.548	1.703	61.554	18.574	0.969	5.129	3.992	0.814
Units	log(FTE)	log(FTE)	log(Patients)	log(Stations)	-	-	-	-
Year FE	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a facility-year. Sample includes facilities involved in an independent-to-chain acquisition and facilities which are independent or owned by the same chain for the entirety of our sample. We drop observations in the year of acquisition. FTE are Full-Time Equivalents. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

4.3 Patient Outcomes

The richness of our data, along with the clinical and operational links between drugs and facility inputs, allows us to connect the changes in strategy at an acquired facility to its effects on patient outcomes. In this way, we can demonstrate how acquisitions directly impact the quality of care received by patients and the cost of this care for Medicare.

We begin by considering a number of clinical outcomes. The first five columns of Table 7 show the effect of acquisitions on patients' urea reduction ratio (URR) and hemoglobin (HGB) levels, two important diagnostic measures for dialysis patients. The dependent variable in column (1) of Table 7 measures the probability that a patient's URR reaches 0.65, the lower bound of how much urea should be removed from a patient's blood during a dialysis session according to accepted standards of care (see Section 2.1 for details). We find a 2.1% increase in the probability that a patient has an adequate URR following acquisition, one of the few cases where quality improves at independent facilities after being acquired by a chain.

In columns (2)-(5) of Table 7, we examine how acquisitions affect patients' management of anemia, focusing on a variety of HGB measures. We find that hemoglobin levels at acquired facil-

ities increase by 1%, which may be beneficial for patients if it pushes them into the recommended range. Looking more closely at the thresholds for high and low HGB, we find decreases in the likelihood that patients have good (5.1%) or low hemoglobin (12.2%), and a 10.0% increase in the likelihood of having hemoglobin above the recommended upper limit of 12 g/dL.

The overall increase in HGB is consistent with our finding above that acquired facilities substantially increase their use of EPO, which treats anemia by increasing HGB. Nephrologists have informed us that there is no clear consensus on whether having low or high hemoglobin is worse for patients, as their respective negative effects are largely incomparable.[29] Having low hemoglobin diminishes a patient's quality of life (e.g., by causing chronic fatigue) and in extreme cases can lead to death and hospitalization. High hemoglobin levels can also increase a patient's risk of cardiac events and death, though through different mechanisms. Despite this ambiguity, CMS weighted high hemoglobin twice as heavily as low hemoglobin when computing scores for a quality incentive program in 2012 (after our sample period). In addition, low hemoglobin has since been dropped as a relevant quality measure by CMS, whereas high hemoglobin is still monitored closely. In our view, this suggests that the increase in hemoglobin values at acquired facilities may, on net, represent a decline in the quality of care received by patients.

Hospitalizations represent another indicator of a facility's overall quality. Columns (6)-(8) of Table 7 show the results from estimating our primary specification where the dependent variable is equal to 1 if a patient was hospitalized for a given cause during the month and 0 otherwise.[30] Our estimates indicate that patients are more likely to be hospitalized, both for any cause and for several individual causes, with all-cause hospitalization rates increasing by 4.2%.

For septicemia, the blood infection common among dialysis patients, we find that patients are 10.0% more likely to be hospitalized following an acquisition. Because these infections are avoidable through the proper cleaning and disinfecting of dialysis machines between patients (Patel et al., 2013), we consider the two most likely explanations for the higher rate of infections following a takeover to be (i) the decrease in per-patient staffing levels at acquired facilities, which leave employees with less time to properly clean machines between patients (column (7)

[29] See Foley (2006) for a complete discussion of this issue.

[30] Episodes of hospitalization are assigned to the month in which they begin.

Table 7: Acquisition Effects on Outcomes

	Clinical Outcomes					Hospitalized			
	(1) URR Good	(2) HGB	(3) HGB Good	(4) HGB Low	(5) HGB High	(6) Any Cause	(7) Sept.	(8) Cardiac Event	(9) Payments Per-Session
Post-Acquisition	0.0183***	0.00992***	-0.0266**	-0.0116***	0.0382***	0.00599***	0.000746**	0.000616	0.0665***
	(0.00496)	(0.00277)	(0.00825)	(0.00307)	(0.00899)	(0.00170)	(0.000261)	(0.000592)	(0.00617)
Observations	14,161,244	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,243
Dep. Var. Mean	0.881	2.449	0.523	0.095	0.382	0.141	0.007	0.030	5.150
Units	pp	log(g/dL)	pp	pp	pp	pp	pp	pp	log($)
Year x Month FE	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Hemoglobin specifications have different observations because it is not submitted with non-ESA claims for most of our sample. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Payments are winsorized at the 99th percentile. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

of Table 6) and (ii) the relative increase in the use of lower-skilled employees who may be less likely to follow proper cleaning and treatment protocols (column (5) of Table 6).

For our final type of hospitalization, we estimate that patients are 2.1% more likely to be hospitalized for an adverse cardiac event following acquisition, although this effect is not statistically significant at the 5% level (p-value of 0.298).[31] Such an increase would be expected given the much larger EPO doses received by patients post acquisition (Table 4), as the principal risk of elevated hemoglobin values (column (5) of Table 7) is a higher incidence of adverse cardiovascular events.

We next consider kidney transplants and waitlists. As discussed above, the most-preferred treatment for ESRD is a kidney transplant. A shortage of available kidneys, however, means that patients must first join a waitlist before receiving a transplant.[32] The process for receiving a kidney transplant is complicated and involves a number of different parties, including a patient's dialysis facility and a kidney transplant team. Regulations require dialysis facilities to educate patients with ESRD about all treatment options, including a kidney transplant. Additionally, to start the transplant process, patients receiving dialysis typically require a referral from their dialysis facility for an evaluation of whether a kidney transplant would be appropriate for them. As such, the proportion of patients referred for a transplant is viewed as an important measure of a facility's quality.[33]

Table 8 presents results from estimating equation (1) with an indicator for whether an incident patient was waitlisted or transplanted within a given time frame as the dependent variable. After acquisition, new patients are less likely to be placed on a transplant waitlist or to receive a transplant during any of the time frames we study. One year after starting dialysis, a new patient at an acquired facility is 8.5% less likely to receive a transplant or be on the waitlist for a transplant than he or she would have been at the same facility before it was acquired. We also find consistent effects after both 180 and 730 days, with patients respectively 8.4% and 9.0% less likely to be placed on the waitlist or receive a transplant by the end of those periods.

[31] It is worth noting that the estimate is statistically significant when we include patient fixed effects, suggesting that unobservable patient characteristics play an important role in cardiac events. See Table 16 in Appendix C.

[32] A patient can receive a transplant without ever being on a waitlist if they receive a living donor transplant.

[33] See Patzer et al. (2015) for much more on the relationship between kidney transplants and dialysis facilities.

Table 8: Acquisition Effects on Waitlisting and Receiving Transplant

	Waitlisted or Transplanted Within:		
	(1) 180 Days	(2) 365 Days	(3) 730 Days
Post-Acquisition	-0.00568*	-0.0108*	-0.0188*
	(0.00288)	(0.00468)	(0.00738)
Observations	690,391	610,955	498,056
Dep. Var. Mean	0.068	0.127	0.208
Units	pp	pp	pp
Year FE	X	X	X
Pat. & Fac. Controls	X	X	X
Facility FE	X	X	X

Notes: Estimates from OLS regression. Facility-clustered standard errors in parentheses. An observation is a new dialysis patient. Sample includes new patients starting dialysis at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop any patients who start dialysis at facilities acquired within six months of acquisition. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Although we interpret these results as another example of acquisitions resulting in worse care for patients, an important limitation of this analysis is that we cannot discern what leads to the decline in transplants. It could be that acquired facilities are less likely to refer their patients for transplants; or, patients could be referred at the same rate but rejected more often by a transplant center. To partially address this, we include a large number of patient characteristics that are likely to affect his or her suitability for a transplant, but there remain unobserved factors, such as the ability to make appointments or comply with doctors' directives.[34] Ideally, we would include patient fixed effects to control for such factors, but this is not possible because each patient is observed only once in this specification. In any event, both explanations have the same implication for patients: an acquisition of their independent facility by a chain makes them less likely to receive a transplant.[35]

As a final measure of quality, we consider patients' survival rates. Table 9 presents estimates

[34]Discussions with nephrologists have informed us that patients can be denied a transplant if they miss appointments, as transplant centers may view them as unlikely to follow through with the care necessary for post-transplant recovery.

[35]There is a small but growing literature on the distinction between waitlisting and referral, such as Patzer et al. (2015). To our knowledge, none of these papers have examined the effects of chain ownership or acquisitions.

of an acquisition's effect on patients' survival rates after 180, 365, and 730 days since starting dialysis. We restrict our attention to patients starting dialysis at facilities that do not change ownership or for whom the entire observation window is before or after acquisition (e.g., to be included in the 180-day specification, a patient must start dialysis more than 180 days prior to the acquisition date). We further restrict our attention to those patients who remain at the same facility until their date of death or the end of the observation window.[36] We find that patients' 365-day survival rate decreases by 1.27 percentage points, or 1.7%. In addition, we see significant decreases after both 180 and 730 days, with patient survival rates falling by 1.3% and 2.9%, respectively.

When considering the totality of our results for clinical outcomes, hospitalizations, transplants, and survival, the overarching finding is that acquisitions result in worse care for patients. But providing high-quality care is costly, so it remains possible that these acquisitions could reduce overall spending on dialysis, making the overall impact on welfare inconclusive. We do not find evidence that acquisitions reduce Medicare expenditures in the dialysis industry, however, as the final column of Table 7 shows that acquired facilities increase their per-session Medicare reimbursements by 6.9%, amounting to $252.4 million in additional spending for Medicare throughout our sample. In short, we find that acquisitions lead to clear changes in firm strategy that substantially worsen the quality of care received by patients and increase the cost of care borne by Medicare.

4.4 Patient Selection

Although the results above are robust to controlling for patient observables and (where feasible) patient fixed effects, we also consider whether a facility changes its mix of patients following an acquisition for two reasons. First, if observable patient attributes at a facility change post acquisition, it may suggest that selection on unobservables could be biasing our results. Second, the ability of chains to selectively treat desirable patients may be an important strategy in and

[36] We have done robustness checks estimating these effects including all patients as well as those who return to the facility within 30 or 60 days, finding similar results.

Table 9: Acquisition Effects on Patient Survival Rates

	Survives for:		
	(1) 180 Days	(2) 365 Days	(3) 730 Days
Post-Acquisition	-0.0107**	-0.0127**	-0.0174**
	(0.00347)	(0.00476)	(0.00654)
Observations	609,960	539,487	457,184
Dep. Var. Mean	0.844	0.746	0.597
Units	pp	pp	pp
Year FE	X	X	X
Pat. & Fac. Controls	X	X	X
Facility FE	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a new dialysis patient. Sample includes new patients starting dialysis at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop any patients who start dialysis at facilities acquired within six months of acquisition. We only include those patients who remain at their original facility until death or the end of the observation window. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

of itself, often referred to as "cream skimming."

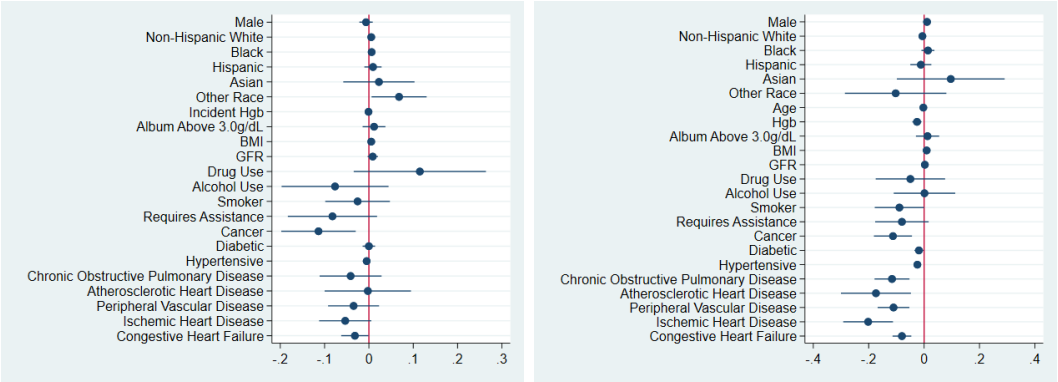
To conduct this analysis, we estimate a series of difference-in-differences specifications with facility and time fixed effects, where the dependent variables are the patient-level controls from the previous specifications, as displayed in equation (4):

$$X_{ijt} = \beta^{Post} D_{jt}^{Post} + \gamma_j + \delta_t + \epsilon_{ijt}. \tag{4}$$

We estimate this specification for both the main patient-month sample as well as a sample restricted to patients in their first month on dialysis, with the results presented in Figure 6. Each plot displays the coefficient estimates of β^{Post} along with 95% confidence bands, all rescaled by the mean of their respective variables.

As shown in Figure 6a, we do not find systematic evidence of cream skimming in the monthly data. In Figure 6b, however, we do find some slight evidence that the characteristics of new patients change following an acquisition. In both cases, the changes are unequivocally in the

direction of healthier patients despite our finding of worse patient outcomes overall. For example, new patients at acquired facilities are less likely to have a variety of comorbid conditions, such as diabetes, hypertension, cancer, and heart disease. If these observable patient attributes are correlated with unobservable attributes, then our results suggest that selection would likely bias our findings of worse outcomes towards zero, making them conservative.



(a) Monthly Patients (b) New Patients

Figure 6: Changes in Patient Mix After Acquisition

Notes: Depicts difference-in-differences estimates of the changes in covariates after acquisition. Estimates are acquisition effects from equation (4). All values are rescaled by the sample mean of their respective covariates. Bars are 95% confidence bands. Standard errors are clustered at the facility level.

5 The Effect of Competition on Firm Behavior

In this section, we investigate whether competition from other dialysis firms can discipline the behavior of newly acquired facilities. With the price for most dialysis treatments fixed by Medicare, facilities may compete for patients by offering higher-quality treatments or other services. Such competition may prevent the acquirer from implementing its strategies to increase profits if patients respond to the corresponding decline in quality by defecting to a rival facility. In what follows, we find no evidence that market concentration mitigates the transference of firm strategy in the dialysis industry. In this way, our findings echo those of Cutler et al. (2017), who, using a different identification strategy and more-aggregate data, also find no evidence that increased concentration from national mergers affects the quality of care received by dialysis patients. We argue below that a key reason that competition does not affect facilities' behavior is that patients

rarely respond to differences in quality, as reflected in the low number of patients who switch facilities each year.

To investigate the effect of concentration on firm behavior, we must first establish a relevant geographic market and then select an appropriate measure of concentration. The existing literature lacks a clear consensus on how to define markets for the dialysis industry — Cutler et al. (2017) and Grieco and McDevitt (2017) define markets as Hospital Service Areas (HSAs); Wilson (2016a) and Dai (2014) use counties; and Wilson (2016b) and Eliason (2019) develop facility-specific markets using distance bands around each facility. In light of this, we focus below on a specification that defines markets as HSAs and uses HHI to measure concentration but show in Appendix E that our results are robust to a variety of other market definitions and measures of concentration.

5.1 Most Acquisitions Do Not Change Market Concentration

We begin by examining whether the acquisitions of independent facilities by chains actually affect market concentration. We first locate market-months where an acquisition will occur in the following month, finding 891 such instances.[37] We then calculate the HHI for that market and what the HHI would have been if the acquisition had already occurred.[38]

Figure 7 shows a scatterplot of pre- and post-acquisition HHI for each HSA-month where an acquisition is about to occur (we reduced the transparency of each dot to 30% so that darker regions imply more overlapping markets or more mass in that area). HHI increases in only 34.4% of HSA-months following an acquisition.[39]

That HHI increases in so few markets following a takeover strongly suggests that changes in facility behavior and patient outcomes are not driven by changes in market concentration. To this point, we find that our results are quantitatively very similar to those in Section 4 when we restrict our sample to markets with only one facility, meaning that the results for these markets

[37] This is less than the total acquisitions due to HSA-months where multiple facilities are acquired.

[38] We use this as our definition of post-acquisition HHI to avoid confounding the effect of acquisition with the entry of new dialysis facilities.

[39] Note that 32.6% of markets where acquisitions occur have only one facility, denoted by the mass at (1,1) in the figure.

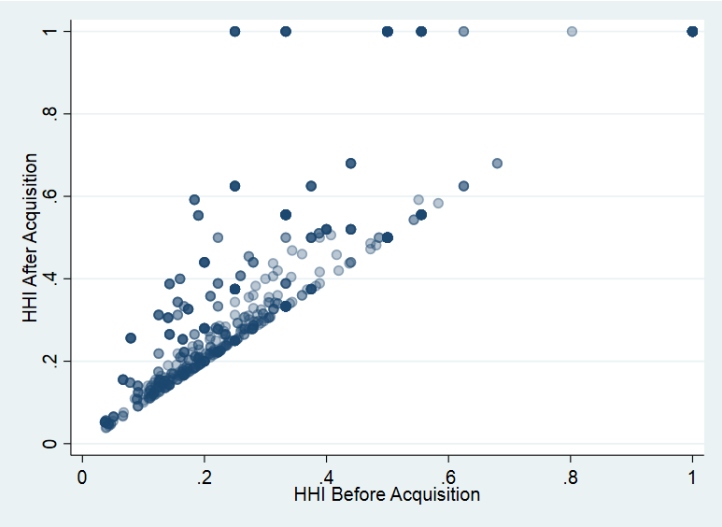


Figure 7: Changes in Concentration Across Markets

Notes: An observation is an acquisition. The horizontal axis depicts the Hospital Service Area's HHI before acquisition. The vertical axis depicts what the Hospital Service Area's HHI would have been in the month before acquisition had the facility already been acquired. Opacity is reduced to 30%, so darker regions represent regions of more mass.

could not possibly be explained by changes in concentration.[40] Rather, firm strategy appears to be the main determining factor.

5.2 Acquisitions That Increase HHI Have Similar Effects

Next, we show in Table 10 that the outcomes in markets where an acquisition increased concentration do not differ from those where an acquisition did not affect market concentration. To do so, we modify our baseline specification by interacting our post-acquisition dummy variable with a dummy variable for whether the acquisition of that facility increased HHI in the market, defined here as an HSA.[41] Formally, this estimating equation is

$$Y_{ijt} = \beta^{Post} D_{jt}^{Post} + \gamma D_{jt}^{Post} \times IncreasesHHI_j + \alpha X_{ijt} + \epsilon_{ijt}, \tag{5}$$

[40] See Table 27 in Appendix E.

[41] In Appendix E, we show that our results are robust to other measures of concentration beyond HHI, a continuous measure of the change in HHI, and other market definitions.

where $IncreasesHHI_j$ is a dummy variable indicating if the acquisition of facility j increased the market's HHI. The effects in Table 10 are not substantially different from our baseline results, either qualitatively or quantitatively. On septicemia hospitalizations, we lose statistical significance, but the point estimate is similar. In addition, we see no effect on the indicator variable for acquisitions that increase HHI, implying that the changes in outcomes we see after an acquisition are not driven by changes in market concentration, leaving changes in management practices as the most likely explanation. As mentioned above, we provide further support for this result in Table 27 in Appendix E, which shows in a sample restricted to markets with only one facility (so that there can be no change in concentration following an acquisition) that the effects of acquisitions are very similar to the baseline results. Further, Table 28 in Appendix E shows that even in markets that are deemed "non-worrisome" by antitrust agencies due to their low levels of concentration and/or the small changes in HHI resulting from the acquisition, we find very similar effects from acquisitions.

A noteworthy implication of these results is that consolidation can have detrimental effects irrespective of market concentration. As acquisitions lead to fewer active firms nationwide, the strategies and management practices of the expanding firms may increasingly affect aggregate outcomes. In this case, acquisitions drive both concentration and a decrease in the quality of care, but the channel through which the latter occurs is the transference of firm strategy, not an increase in market power.

5.3 Why Competition Does Not Discipline Provider Behavior

In regulated markets, standard models of competition (e.g., Gaynor (2004) and the models discussed therein) with endogenous provider quality predict that quality will increase with the extent of competition in the market. This theoretical result relies on the assumption that demand increases with product quality, which in our setting would mean that patients are more likely to choose a high-quality facility, all else equal, and thus facilities would compete for patients by offering higher-quality care. In practice, patient demand in the U.S. dialysis market does not respond to the decline in quality following an acquisition. As suggested in column (7) of Table

Table 10: Acquisition Effects By Concentration Increase: HSA Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.808***	0.553***	-0.286**	0.0112*	-0.0123*	0.0436***	-0.0313**	0.0174*	0.00800**	0.000433	0.000924*
	(0.0752)	(0.123)	(0.100)	(0.00441)	(0.00533)	(0.0120)	(0.0112)	(0.00708)	(0.00250)	(0.000912)	(0.000409)
Post-Acquisition ×	-0.0486	0.0891	-0.0267	-0.00202	0.00120	-0.00867	0.00747	0.00156	-0.00318	0.000289	-0.000283
Increases HSA HHI	(0.0823)	(0.151)	(0.124)	(0.00526)	(0.00614)	(0.0163)	(0.0153)	(0.00893)	(0.00324)	(0.00114)	(0.000499)
Patient-Months	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Units	log(UI)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Pat. & Fac Controls	X	X	X	X	X	X	X	X	X	X	X
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. The number of observations differs from the baseline specification due to missing ZIP Code-to-market crosswalk data. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

6, acquired facilities are actually able to increase the number of patients they treat per machine despite providing lower-quality treatments.

We look more directly at this result by considering whether patients are more likely to switch away from a facility after it is acquired, finding that they are not. In general, it is uncommon for dialysis patients to switch providers, where 98.4% of patient-months in our sample have the patient visiting the same facility the following month. Additionally, those who do switch tend to be newer dialysis patients: 36.3% of switches are patients in their first 12 months of dialysis, while those patients make up only 24.6% of observations overall. Patients in their first 12 months of dialysis likely make up a disproportionate share of switches due to the capacity constraints described in Eliason (2019), where new patients choose the best facility that has available capacity and then switch to their most-desired facility when a free space opens up there. Moreover, 19.9% of switchers eventually return to the facility from which they switched. Patients who return to their initial facility are typically people who travel to another location, such as for vacation, and are unable to visit their original facility. Since they return, it is unlikely their behavior reflects a concern about the facility's quality. For patients who have completed 12 months of dialysis, only 1.3% of patient-months represent a permanent switch away from a facility.

In addition to the low absolute levels of switching among patients, we show in Table 11 that patients do not become more likely to switch after their facility is acquired. For the full sample of patients, our point estimate of the effect of acquisition on switching is -0.06 percentage points, which is small economically and not statistically significant at conventional levels. In addition, we find that acquisitions do not have a meaningful impact on patients' likelihood of switching in their first year or if we only include facility switches where the patient does not return to his or her initial facility.

A host of institutional and behavioral factors explain why patients do not switch from low-quality providers. In many markets, patients may not have a valid outside option, as one-third of markets in our sample have only 1 facility. Our findings are unchanged, however, if we repeat the analysis in Table 11 but restrict our sample to include only markets with at least two facilities.[42]

[42]Results available upon request.

Table 11: Effect of Acquisition on Facility Switching

	All		First Year	
	(1) Any	(2) Never Return	(3) Any	(4) Never Return
Post-Acquisition	-0.000707	-0.000467	-0.000384	-0.000300
	(0.000507)	(0.000454)	(0.000847)	(0.000772)
Observations	13,898,240	13,898,240	3,416,860	3,416,860
Dep. Var. Mean	0.016	0.013	0.024	0.020

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Columns (3) and (4) include only patients in their first 12 months on dialysis. The dependent variable in columns (1) and (2) is 1 if the patient is on dialysis the next month at a different facility and 0 if they remain on dialysis at their current facility. The dependent variable in columns (2) and (4) is 1 only for those patients who do not return to the initial facility at any point in our sample. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Moreover, even patients who live in markets with multiple facilities face significant travel costs due to the frequency of visits required for dialysis, as documented in Eliason (2019). These travel costs are exacerbated by comorbidities that make travel difficult as well as the low income of most dialysis patients. As such, travel costs may outweigh concerns about a facility's quality for most patients. Behavioral inertia likely also plays a significant role in this market, as it does in other health-care settings (e.g., Handel, 2013). Tilipman (2018) in particular finds that patients exhibit significant loyalty to their physicians, and the physicians to whom they are the most loyal are their primary care doctors. As dialysis facilities are the primary source of health care for many dialysis patients, the significant inertia in their choice of a provider is in line with such findings.

6 Understanding Pre-Acquisition Differences Across Chain and Independent Facilities

In the analysis above, we demonstrated that the effects of an acquisition persist even when it is not accompanied by a change in market structure, such as when an independent facility with

a monopoly in its market is acquired by a chain. In almost all cases, we find that independent facilities acquired by chains had better patient outcomes but lower profits than chain facilities prior to acquisition. Shortly after acquisition, the chains implement new policies regarding, for instance, the facilities' drug doses and staffing levels, which then lead to higher profits but worse outcomes for patients. Because competitive pressure does not explain why independent facilities do not imitate the behavior of the more-profitable chain facilities before being acquired, as shown in Section 5, in this section we explore several alternative explanations. We find the most prominent reason relates to differences in the potential tradeoffs facilities face regarding maximizing their own profits and maintaining high standards of care, which stem primarily from differences in economies of scale for purchasing injectable drugs.

To conduct this analysis, we supplement the USRDS data with data from HCRIS that include accounting costs for key facility inputs, such as EPO, which allows us to better understand the differences in facilities' costs and why they might behave differently. We estimate the impact of an acquisition on total variable profits per dialysis session and several variables related to EPO using the following specification:

$$Y_{jt} = \beta^{Pre} D_{jt}^{Pre} + \beta^{Post} D_{jt}^{Post} + \beta^{Chain} D_{jt}^{Chain} + \alpha X_{jt} + \epsilon_{jt}, \tag{6}$$

where X includes state and year fixed effects. From the results presented in Table 12, we find no evidence that chains disproportionately acquire the least-sophisticated or worst-performing independent facilities to turn around, unlike in other settings where sharply declining financial performance prompts an ownership change (Brav et al., 2015). That is, acquired independents are no less profitable than the independents that are not acquired.[43] Column (1) shows that, on average, independent facilities that are eventually acquired earned a statistically insignificant $1.36 more in variable profits per session (these exclude fixed costs such as rent[44]) before acquisition

[43] If anything, acquired independents were behaving slightly more like for-profit chains prior to acquisition with respect to EPO doses, as shown in columns (1) and (2) of Table 4), meaning that there were likely fewer profitable opportunities to increase patients' doses following acquisition.

[44] Although these data are useful for understanding why firms may have been "leaving money on the table" prior to acquisition, the distinction between fixed and variable costs is not always transparent, so we have restricted our analysis to cases where we have a clear understanding of this accounting, such as with injectable drugs.

compared to the omitted group, independent facilities that are never acquired. After acquisition, per-session variable profits increase by \$16.81 (= \$18.17 – \$1.36) at the acquired independent facilities.[45] This suggests that chains do not selectively acquire low-performing independent facilities; rather, both acquired and not-acquired independent facilities had similar profits prior to acquisition. After acquisition, the new owners then improve the financial performance of their targets, similar to what Braguinsky et al. (2015) found in their setting.

Most of the increase in per-session profits at acquired facilities comes from EPO. Column (2) of Table 12 shows that the profits from EPO increase by \$8.43 per session, or 50.1% of the total increase in profits shown in column (1). EPO is more profitable for chains in part because they pay lower prices for the drug, as shown in column (3), which reflects the volume discounts they negotiate with drug manufacturers such as Amgen. For example, in DaVita's 2005 Annual Report, the company writes, "Our agreement with Amgen for the purchase of EPO includes volume discounts and other thresholds which could negatively impact our earnings if we are unable to meet those thresholds." Also, "Our contract with Amgen provides for specific rebates and incentives that are based on ... purchase volume growth." Facing lower costs for EPO, chains use more of it, as shown in column (4), so total EPO expenditures differ little after acquisition, as shown in column (5).

The scale economies stemming from buyer power are not available to smaller independent facilities, and this is a key reason why their behavior differs from chains' prior to acquisition. If independent providers treated patients with the same doses that the largest chains do, they would earn only 55% of the profits due to their higher wholesale costs for EPO while presumably facing the same risks and non-pecuniary costs associated with those high doses, such as an elevated risk of cardiac events.[46] If providers balance the financial gains of giving patients larger EPO doses against the risks and non-pecuniary costs of doing so, this difference in per-unit costs may lead chains to administer more EPO to their patients. That is to say, these cost differences may

[45] The difference is \$17.73 based on a specification with facility fixed effects. We focus on the specifications without facility fixed effects because they allow us to compare the pre-acquisition profits of acquired facilities to the profits of facilities that were never acquired.

[46] This assumes that Medicare reimburses \$10 per 1000 IUs of EPO, which is a close approximation of the actual rate during the study period: $\frac{10-(9.19-0.37)}{10-(9.19-1.34)} = 0.5488$.

Table 12: Effect of Chain Acquisition on Profit Measures

	(1) Variable Profits per Session	(2) EPO Margin	(3) EPO Cost Per 1000 IUs	(4) EPO Units per Session	(5) Total EPO Costs
Pre-Acq	1.360	-0.581	-0.371**	222.5	-0.451
	(2.497)	(1.652)	(0.141)	(204.1)	(1.723)
Post-Acq	18.17***	7.851***	-1.237***	778.8***	0.965
	(2.205)	(1.334)	(0.145)	(171.9)	(1.464)
Always Chain	22.16***	7.975***	-1.340***	812.2***	0.745
	(2.344)	(1.626)	(0.156)	(193.4)	(1.724)
Constant	30.60***	1.113	9.190***	3835.8***	35.36***
	(3.704)	(3.399)	(0.205)	(265.7)	(2.833)
Year FE	X	X	X	X	X
State FE	X	X	X	X	X
Observations	25,934	25,934	25,934	25,934	25,934
Post - Pre	16.81	8.432	-0.866	556.3	1.416
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.0720]
Always Chain - Post	3.993	0.123	-0.103	33.42	-0.220
P-value	[0.002]	[0.880]	[0.000]	[0.732]	[0.806]

Notes: Facility-clustered standard errors in parentheses. An observation is a facility-year. Sample includes facilities involved in an independent-to-chain acquisition and facilities that are independent or owned by the same chain for the entirety of our sample. We drop observations in the year of acquisition and those cost reports that are for fewer than 365 days. EPO margin is calculated as the average national payment rate per 1000 IU less the costs from the cost reports. Top panel shows coefficient estimates from equation (6). Bottom panel shows estimated difference between post-acquisition and pre-acquisition coefficients and always chain and post-acquisition coefficients, along with p-values. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

induce different dosing strategies even if chains and independents are both seeking to maximize their profits.[47]

Another possible explanation for why independent and chain facilities behave differently is that chains may have different underlying objectives, perhaps focusing more on financial performance than on patient outcomes. One way to proxy for the incentives that a firm faces is its for-profit status. Because the largest chains are for-profit firms and many independent facilities

[47]The result that newly acquired independents benefit from chain-level economies of scale contrasts somewhat with the results of Blonigen and Pierce (2016), who find little evidence of merger efficiencies in U.S. manufacturing.

are non-profit, the change in for-profit status following an acquisition may explain the changes in behavior and outcomes rather than the change in ownership itself. A related argument is made by Eaton et al. (2018), who show that the high-powered incentives introduced by private equity owners following takeovers in higher education lead to better financial performance but worse student outcomes. We explore this possibility in Appendix D, finding in Tables 17 and 18 that the post-acquisition changes across most of our measures are largely the same for all acquired independent facilities, regardless of whether they were previously non-profit or for-profit. There are a few notable exceptions to this: the effects of acquisition on EPO and Venofer doses, as well as the use of technicians, are all smaller in the case of for-profit independent facilities. The effect is diminished primarily because for-profit independent facilities were already behaving more like chains along these dimensions before they were acquired, suggesting that changes in for-profit status may account for some portion of our results. At the same time, these differences are relatively small, suggesting that the effects arising from a change in for-profit status are secondary to the effects from a change in ownership.[48]

In addition, chains' behavior might seem risky given the potential negative impacts on patient care resulting from excessive drug doses or low staffing levels. Chains may be more willing than independent facilities to accept this risk if they have large financial reserves to pay for any future litigation, allowing them to behave in ways that increase their profits even if it makes it more likely they will face malpractice lawsuits. Although we have not found any direct evidence that this drives their behavior, it is worth noting that chains have indeed been subject to numerous lawsuits, with DaVita alone making at least four settlements exceeding $100 million in the last 10 years.

Other possible explanations for the differences in behavior between independent and chain facilities lack empirical support. For example, we showed above in Section 4.4 that chain and independent facilities treat a very similar distribution of patients, so it is unlikely that a change in patient mix following a takeover alters a target's behavior. Another possible explanation is that chains may be subject to different regulations than independent facilities, but both types

[48]These results are in line with those of Duggan (2000), who finds evidence that non-profit hospitals are no more altruistic than for-profit ones.

of facilities face the same regulatory environment, such as Medicare reimbursement rates and certification standards. Given the lack of support for these alternative explanations, we conclude that a leading explanation for why independent facilities do not employ the same strategies as chains is that they face different tradeoffs when balancing profits and patient care, the majority of which arise from differences in economies of scale.

7 Conclusion

Changes in ownership affect the treatment and outcomes of patients at independent dialysis facilities acquired by chains. Our results show that acquired facilities change their behavior in three broad ways, each of which either increases their revenue or decreases their operating costs. First, acquired facilities capture higher per-session reimbursements from Medicare by increasing drug doses and shifting to more-lucrative drugs. Second, acquired facilities stretch their resources by treating more patients relative to the number of staff and stations at the facility. Third, acquired facilities reduce their costs of providing dialysis treatment by replacing high-skill nurses with lower-skill technicians.

Adopting the acquirer's strategies causes the acquired facility's quality of care to decline. Along almost every dimension we measure, patients fare worse at the target facility after acquisition, most prominently in terms of fewer kidney transplants, more hospitalizations, and lower survival rates. Because Medicare spends more after acquired facilities implement their strategic changes, the diminished quality represents an unambiguous decline in the overall value of dialysis treatments, although more research is needed to understand the implications for total welfare, as these acquisition may promote access to dialysis in underserved markets (Eliason et al., 2019a).

Our results may have important policy implications, as the acquisitions we study throughout this paper were all permitted by antitrust authorities. As noted in Wollmann (2018), mergers and acquisitions in fragmented industries, such as dialysis, often escape regulatory enforcement because they tend to fall below the Hart-Scott-Rodino threshold of $50 million. Such "stealth consolidation" occurs as large firms progressively buy up smaller firms, absorbing them into their

organizations and resulting in greater industry concentration. This phenomenon has recently occurred elsewhere in health care, such as among physician practices (Capps et al., 2017), and in a wide variety of other industries (see Wollmann (2018) and *The Economist* (2015) for examples). Although more research is needed to understand the full implications of these trends, many policymakers have raised concerns about the potential harm they may impose on consumers. Calls to reform the current standards include lowering the current Hart-Scott-Rodino threshold and having an automated review process for comparatively small deals (Scott-Morton, 2019).

Although most acquisitions of dialysis facilities fall outside the scope of current antitrust laws, which prohibit acquisitions if "the effect of such acquisition may be substantially to lessen competition, or to tend to create a monopoly" (U.S. Department of Justice and Federal Trade Commission, 2010), our paper shows that these transactions still have severe consequences for patients. Our results persist even in cases where the acquisition does not affect market structure, such as acquisitions in markets with only one facility and in markets that are deemed non-worrisome by the Horizontal Merger Guidelines. To the extent that the diffusion of firm strategy is the primary mechanism through which acquisitions cause the quality of dialysis care to decline, minor adjustments to the current antitrust statutes in the U.S. may do little to prevent the harmful effects of these acquisitions.

One policy prescription would be to avoid enacting regulations that could unintentionally spur consolidation, such as certificate of need laws, which make new entry more difficult for expanding health-care providers and lead them to favor acquisitions instead (Pozniak et al., 2010). Others have raised concerns that policies that increase the administrative burdens for facilities may inadvertently increase consolidation (Gaynor, 2018). Aspects of Medicare's reimbursement policies may also lead to greater consolidation. By tying each firm's reimbursements to the costs of comparable firms, regulators encourage cost minimization through "yardstick competition" (Shleifer, 1985), which may increase the pressure to consolidate if greater economies of scale are necessary to decrease costs and maintain high profit margins. Similarly, the uniform fee-for-service reimbursement policy for injectable drugs may also contribute to consolidation, as it favors large firms that can negotiate lower prices for drugs. Although each of these policies likely

has beneficial aspects, their tendency to drive consolidation should nevertheless be viewed as a tradeoff against those benefits.

Our results also illustrate the importance of well-designed payment systems in controlling health-care costs and improving patient outcomes. As we show in the case of EPO, poorly structured reimbursement schemes can induce provider behavior that not only wastes resources, but also harms patients. By improving the design of Medicare's payment systems, policymakers can simultaneously reduce costs and improve outcomes. Some changes in this direction have already occurred. In 2011, for example, Medicare bundled payments for dialysis treatments and their associated injectable drugs into a single Prospective Payment System, which effectively reduced providers' financial incentives to overuse EPO. To address the resulting incentive to use too little EPO, the Quality Incentive Program initiated in 2012 allows Medicare to penalize providers that fail to meet certain quality standards: providers that have too many patients below the benchmark for hemoglobin levels, for example, could lose up to 2% of their entire reimbursement from Medicare. Although these changes would seem to improve facilities' incentives for providing high-quality and cost-effective care, more research is needed to understand how they have changed the industry and affected patients (Eliason et al., 2019b).

Finally, because dialysis is a market in which the government, via Medicare, plays an outsize role in subsidizing care and in which patients may find it difficult to observe their facilities' quality, competition may be unlikely to discipline providers' behavior. Our findings are therefore likely to be applicable to similar settings in other areas of health care or higher education. Indeed, Eaton et al. (2018) show that private equity buyouts in higher education lead to higher tuition and per-student debt, while at the same time resulting in lower graduation rates, loan repayment rates, and earnings among graduates. Complementing this result, Bernstein and Sheen (2016) find that private equity buyouts of restaurants lead to better health safety ratings, arguably a very visible measure of quality for consumers. As such, future work should consider how the effects of acquisitions differ in markets characterized by extensive government intervention, such as health care and education, compared to those without it, such as restaurants, as well as how these effects differ depending on how well patients or consumers can observe quality.

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APPENDICES

The following appendices provide additional robust checks for our main results and further details on our data:

Appendix A presents another version of Table 2 that includes only observations within 12 months of an acquisition.

Appendix B presents results from a robustness check that does not exclude observations from the year of acquisition.

Appendix C presents results from a robustness check that includes patient fixed effects.

Appendix D considers whether changes in for-profit status can explain changes in facilities' behavior following an acquisition.

Appendix E presents results from a robustness check using alternative measures of markets and concentration, and also looks at markets that experience mergers to monopoly as well as markets that are "non-problematic" for antitrust authorities according to the Horizontal Merger Guidelines.

Appendix F presents results from our main specifications but without patient covariates.

Appendix G provides figures for the remainder of our event studies not included in the main body of the paper.

Appendix H details our process for determining ownership changes and the dates of acquisition.

Appendix I provides supporting evidence of standardization following an acquisition.

A Patient Characteristics Around Acquisition

Table 13 shows a version of Table 2 including only observations within 12 months of an acquisition, where we see the differences between pre- and post-acquisition facilities largely disappear.

Table 13: Patient and Treatment Descriptive Statistics Around Acquisition

	Pre-Acquisition	Post-Acquisition
Clinical Characteristics		
Diabetic (%)	55.01	55.19
Hypertensive (%)	86.19	85.89
BMI	28.21	28.09
GFR	7.94	7.88
Albumin $\geq$ 3.0g/dL (%)	52.50	52.13
Hemoglobin	7.72	7.68
Cancer (%)	5.06	4.99
Drug Use (%)	1.08	1.06
Alcohol Use (%)	1.22	1.23
Smoker (%)	5.60	5.73
Requires Assistance (%)	5.05	4.68
Chronic Obstructive Pulmonary Disease (%)	6.88	6.84
Atherosclerotic Heart Disease (%)	5.86	6.08
Peripheral Vascular Disease (%)	13.93	14.03
Ischemic Heart Disease (%)	17.63	18.68
Congestive Heart Failure (%)	31.59	32.08
Patient Demographics		
Male (%)	52.35	52.74
Non-Hispanic White (%)	47.05	47.31
Black (%)	35.64	34.35
Hispanic (%)	11.35	11.97
Asian (%)	2.66	2.89
Other Race (%)	5.37	5.78
Area Demographics		
% High School	33.08	33.23
% College	7.78	7.70
Median Income	47,667.58	47,796.10
Age	64.28	64.38
Months With ESRD	34.16	32.66
Facility Characteristics		
Facility Age	10.65	7.59
Facility Elevation	190.89	194.75
For-Profit (%)	84.03	94.05
Patient-Months	122,500	153,894

Notes: See text for more detail.
[a] Dummy variable for being waitlisted or transplanted within 1 year for incident patients only.

B Including the 12 Months Surrounding Acquisition

In this appendix, we present our main results from a sample that includes observations from the year of acquisition. The reason we excluded observations surrounding the year of acquisition in the main body of the paper is that the precise date when a facility is acquired may be measured with error, as discussed in Section 3. The results here show that our results are robust to including the year of acquisition. As expected, however, the measurement error we introduce somewhat attenuates the estimated magnitudes.

Table 14: Effect of Acquisition on Per-Treatment EPO Dose

	(1) Epogen	(2) Epogen	(3) Epogen
Pre-Acquisition	0.300*	0.300*	
	(0.131)	(0.121)	
Post-Acquisition	1.466***	1.337***	0.762***
	(0.0863)	(0.0816)	(0.0663)
Always Chain	1.508***	1.345***	
	(0.0841)	(0.0775)	
Observations	14,437,638	14,437,638	14,437,638
Baseline Estimate	1.485	1.350	0.829
Units	log(IU)	log(IU)	log(IU)
Year x Month FE	X	X	X
Pat. & Fac. Controls		X	X
Facility FE			X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We do not drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Baseline estimates are post-acquisition coefficients from Table 4. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 15: Acquisition Effects on Outcomes

	Clinical Outcomes					Hospitalized			
	(1) URR Good	(2) HGB	(3) HGB Good	(4) HGB Low	(5) HGB High	(6) Any Cause	(7) Sept.	(8) Cardiac Event	(9) Payments Per-Session
Post-Acquisition	0.0152***	0.00885***	-0.0283***	-0.00866**	0.0369***	0.00481***	0.000617**	0.000182	0.0551***
	(0.00429)	(0.00259)	(0.00737)	(0.00280)	(0.00796)	(0.00145)	(0.000226)	(0.000502)	(0.00551)
Observations	14,437,638	13,520,140	13,520,140	13,520,140	13,520,140	14,437,638	14,437,638	14,437,638	14,437,637
Baseline Estimate	0.0183	0.0959	-0.0266	-0.0116	0.0382	0.00599	0.000746	0.000616	0.0665
Units	pp	log(g/dL)	pp	pp	pp	pp	pp	pp	log($)
Year x Month FE	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Hemoglobin specifications have different observations because it is not submitted with non-ESA claims for most of our sample. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We do not drop observations within 6 months of the month of acquisition. Payments are winsorized at the 99th percentile. Baseline estimates are post-acquisition coefficients from Table 7. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

C Adding Patient Fixed Effects

In this appendix, we repeat our analysis of the patient-month variables in specifications that include patient fixed effects. Table 16 shows results for patients who stay at a single facility and are treated there both before and after acquisition. These specifications do not include facility fixed effects because they are not separately identified given that each patient receives treatment from only one facility in this sample. We find results consistent with our main specification, with identification of the acquisition effect coming solely from within-patient changes following acquisition.

Table 16: Robustness: Including Patient Fixed Effects

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.845***	0.563***	-0.292***	0.00104	0.00629	-0.0393***	-0.000331	0.0390**	0.0371***	0.00241***	0.00813***
	(0.178)	(0.0937)	(0.0774)	(0.00605)	(0.00386)	(0.0112)	(0.00410)	(0.0123)	(0.00281)	(0.000426)	(0.00106)
Observations	475,694	387,410	418,449	475,694	428,857	428,857	428,857	428,857	475,694	475,694	475,694
Dep. Var. Mean	7.552	1.116	0.676	0.893	2.455	0.534	0.079	0.388	0.108	0.005	0.023
Baseline Estimate	0.829	0.612	-0.303	0.0183	0.0959	-0.0266	-0.0116	0.0382	0.00599	0.000746	0.000616
Dep. Var. Units	log(IU)	log(mg)	log(mg)	pp	log(g/dL)	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Patient FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Hemoglobin specifications have different observations because it is not submitted with non-ESA claims for most of our sample. Sample includes hemodialysis patients who only ever visit a single facility treated at facilities involved in an independent-to-chain acquisition and bridge the date of acquisition. We drop observations within 6 months of the month of acquisition. Specifications include patient, but not facility, fixed effects. Baseline estimates are post-acquisition coefficients from Tables 4-7. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

D Acquisition Effects by For-Profit Status

A possible explanation for why acquisitions affect firm behavior is that chains may have different objectives, perhaps focusing more on financial performance than on patient outcomes. That is, their organizational structure may lead them to focus more on profits because, unlike chains, many independent facilities are non-profit entities. A related argument is made by Eaton et al. (2018), who show that the high-powered incentives introduced by private equity acquisitions in higher education lead to better financial performance for the school but worse outcomes for students. At the start of our data, 30.11% of all facilities are non-profit, and there is only 1 non-profit chain, Dialysis Clinic, Inc. Therefore, if the majority of acquisitions were characterized by for-profit chains buying non-profit facilities, one might expect to see the change in firm incentives manifest itself in patterns like the ones we document above, with 11.88% of the 1,065 acquisitions in our data involving a non-profit facility being acquired by a for-profit chain.

To investigate this, we modify our primary specification to interact acquisition status with the for-profit status of a facility when it was independent:

$$Y_{ijt} = \beta Acquired_{jt} + \eta Acquired_{jt} \times ForProfit_j^{Pre} + \alpha X_{ijt} + \epsilon_{ijt}, \tag{7}$$

where $ForProfit_j^{Pre}$ is a dummy variable for whether facility j was a for-profit facility prior to being acquired. As shown in Tables 17 and 18, the post-acquisition changes across all of our measures are largely the same for acquired independent facilities, regardless of whether they were previously non-profit or for-profit.[49] There are a few notable exceptions to this: the effects of acquisition on EPO and Venofer doses, as well as the use of technicians, are all smaller in the case of for-profit independent facilities. The effect is diminished primarily because for-profit independent facilities were already behaving more like chains along these dimensions, suggesting that changes in for-profit status may account for some portion of our results. Still, these differences are small relative to the acquisition effects experienced by both types of independent facilities. This, together with the fact that for most outcomes we see no significant differences, suggests that the effect of a change in for-profit status is secondary to the overall acquisition effect.

[49] These results are in line with those of Duggan (2000), who finds evidence that non-profit hospitals are no more altruistic than for-profit ones.

Table 17: Heterogeneity in Treatment and Outcome Response by For-Profit Status

	Drugs & Payments				Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Epo	Venofer	Ferrlecit	Payments Per-Session	URR Good	HGB	HGB Good	HGB Low	HGB High	Any Cause	Sept.	Cardiac Event
Post-Acquisition	1.149***	1.007***	-0.433**	0.0482***	-0.00297	0.0123	-0.0192	-0.00896	0.0282	0.0131**	0.00131	0.00274*
	(0.195)	(0.198)	(0.137)	(0.0142)	(0.0101)	(0.00901)	(0.0176)	(0.0104)	(0.0167)	(0.00421)	(0.000723)	(0.00134)
Post-Acquisition x	-0.442*	-0.444*	0.144	0.0258	0.0249*	-0.00224	-0.00757	-0.00399	0.0116	-0.00785	-0.000682	-0.00221
Prev. For-Profit	(0.181)	(0.206)	(0.149)	(0.0153)	(0.0112)	(0.00914)	(0.0203)	(0.0106)	(0.0199)	(0.00452)	(0.000748)	(0.00143)
Observations	13,820,539	11,349,206	12,190,138	13,820,538	13,820,539	12,955,204	12,955,204	12,955,204	12,955,204	13,820,539	13,820,539	13,820,539
Dep. Var. Mean	7.531	1.336	0.588	5.151	0.881	2.449	0.524	0.096	0.381	0.141	0.007	0.030
Units	log(IU)	log(mg)	log(mg)	log($)	pp	log(g/dL)	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X	X
Full Effect p-value	0.000	0.000	0.000	0.000	0.000	0.001	0.006	0.000	0.000	0.005	0.025	0.414

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Hemoglobin specifications have different observations because it is not submitted with non-ESA claims for most of our sample. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Payments and drug doses are winsorized at the 99th percentile. Prev. For-Profit is an indicator for whether the facility was for-profit in the last year prior to acquisition. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 18: Heterogeneity in Facility Inputs, Patient Survival, and Transplantation by For-Profit Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Facility Inputs								Survives			Tx or Waitlist		
	Nurses	Technicians	HD Patients	Stations	Nurses per Technician	Patients per Employee	Patients Per Station	Employees per Station	180 Days	365 Days	730 Days	180 Days	365 Days	730 Days
Post-Acquisition	-0.0159	0.175***	0.115*	0.0446	-0.369**	0.916***	0.0910	0.0257	-0.0178*	-0.0156	-0.0265	0.00308	0.00423	0.00491
	(0.0516)	(0.0494)	(0.0512)	(0.0285)	(0.127)	(0.244)	(0.166)	(0.0412)	(0.00852)	(0.0114)	(0.0163)	(0.00711)	(0.0101)	(0.0185)
Post-Acquisition x	-0.00554	-0.157**	0.0237	-0.0295	0.272*	-0.384	0.112	-0.0664	0.00662	0.00345	0.00850	-0.0118	-0.0209	-0.0342
Prev. For-Profit	(0.0554)	(0.0551)	(0.0540)	(0.0305)	(0.132)	(0.267)	(0.188)	(0.0456)	(0.00918)	(0.0123)	(0.0175)	(0.00748)	(0.0108)	(0.0195)
Observations	24,766	24,766	42,457	42,559	23,116	24,766	42,559	24,766	594,343	525,516	445,030	674,853	597,882	488,743
Dep. Var. Mean	1.548	1.702	3.830	2.835	0.970	5.125	3.984	0.814	0.844	0.746	0.597	0.067	0.127	0.208
Units	log(FTE)	log(FTE)	log(Patients)	log(Stations)	-	-	-	-	pp	pp	pp	pp	pp	pp
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a facility-year in columns (1)-(8), a new patient starting dialysis in all other columns. Sample includes facilities involved in an independent-to-chain acquisition and facilities that are independent or owned by the same chain for the entirety of our sample or patients starting dialysis at those facilities. We drop facility-years in the year of acquisition and new patients whose observation windows overlap with the date of acquisition. FTE are full-time equivalents. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

E Robustness of Competition Results

This appendix demonstrates the robustness of our results from Section 5 to alternative market definitions, continuous changes in HHI, and different measures of competition. We also present results from monopoly markets and markets that the Horizontal Merger Guidelines deem "non-worrisome" that corroborate our baseline results.

Table 10 investigates acquisitions that increase HHI. Table 19 shows that these results are robust to using a continuous measure of how much HHI changes.

We have shown that acquisitions that increase HHI at the HSA level do not differ in their effects on firm behavior. In line with Eliason (2019) and Wilson (2016b), however, many patients seek treatment outside of their HSA, suggesting that these may not be relevant market definitions. Tables 20-23 show that the results are robust to alternative market definitions, including CBSA and several distance-based measures.

The presence of a direct competitor may also affect an acquirer's ability to alter a target's behavior following acquisition. In Tables 24-26, we show that the presence of a competitor within 1, 5, and 10 miles and the number of competitors within 1, 5, and 10 miles do not affect our qualitative findings.

Table 19: Acquisition Effects By HHI Change

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.746***	0.583***	-0.290***	0.00976***	-0.0120***	0.0369***	-0.0249**	0.0182***	0.00561**	0.000394	0.000847**
	(0.0692)	(0.0772)	(0.0627)	(0.00277)	(0.00320)	(0.00852)	(0.00783)	(0.00502)	(0.00178)	(0.000631)	(0.000267)
Post-Acquisitions ×	0.331	0.259	-0.122	0.00180	0.00462	0.0142	-0.0189	0.00137	0.00405	0.00236	-0.00108
Δ HHI	(0.189)	(0.256)	(0.189)	(0.00509)	(0.00739)	(0.0173)	(0.0162)	(0.0123)	(0.00411)	(0.00165)	(0.000670)
Observations	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Dep. Var. Mean	7.538	1.337	0.589	2.449	0.095	0.382	0.523	0.881	0.141	0.030	0.007
Units	log(IU)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. HHI is calculated at the HSA level. Change in HHI is only non-zero for acquired facilities. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 20: Acquisition Effects By Concentration Increase - CBSA Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.854***	0.582***	-0.270*	0.00149	-0.00247	0.0270*	-0.0246*	0.00717	0.00871**	0.000931	0.00153**
	(0.0966)	(0.167)	(0.137)	(0.00385)	(0.00484)	(0.0125)	(0.0118)	(0.00639)	(0.00306)	(0.00102)	(0.000569)
Post-Acquisitions ×	-0.101	0.0388	-0.0432	0.0110*	-0.0119*	0.0145	-0.00263	0.0145	-0.00354	-0.000409	-0.00102
Increases CBSA HHI	(0.0944)	(0.184)	(0.151)	(0.00474)	(0.00580)	(0.0158)	(0.0149)	(0.00821)	(0.00353)	(0.00118)	(0.000622)
Patient-Months	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Units	log(UI)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Pat. & Fac Controls	X	X	X	X	X	X	X	X	X	X	X
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Observations differ from baseline due to missing ZIP Code-to-market crosswalk data. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 21: Acquisition Effects For HHI Increases - 1 Mile Radius Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.765***	0.601***	-0.253***	0.00691*	-0.00983**	0.0261**	-0.0163*	0.0169**	0.00497**	0.000783	0.000664*
	(0.0755)	(0.0875)	(0.0693)	(0.00309)	(0.00357)	(0.00818)	(0.00753)	(0.00588)	(0.00191)	(0.000648)	(0.000323)
Post-Acquisition ×	0.0266	0.0303	-0.139	0.00887	-0.00518	0.0354	-0.0303	0.00415	0.00297	-0.000489	0.000221
Increases 1 Mile HHI	(0.0969)	(0.152)	(0.129)	(0.00548)	(0.00612)	(0.0202)	(0.0190)	(0.00933)	(0.00358)	(0.00128)	(0.000496)
Observations	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Dep. Var. Mean	7.538	1.337	0.589	2.449	0.095	0.382	0.523	0.881	0.141	0.030	0.007
Units	log(IU)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. HHI is facility specific. Each facility denotes a separate market made up of facilities within 1 mile of that facility. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 22: Acquisition Effects For HHI Increases - 5 Mile Radius Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.833***	0.566***	-0.242**	0.00787*	-0.0134**	0.0218*	-0.00839	0.0202**	0.00588*	0.000765	0.000653
	(0.0857)	(0.0999)	(0.0784)	(0.00375)	(0.00439)	(0.00974)	(0.00915)	(0.00677)	(0.00233)	(0.000803)	(0.000392)
Post-Acquisition ×	-0.111	0.0800	-0.109	0.00391	0.00334	0.0311	-0.0344*	-0.00358	0.000200	-0.000281	0.000162
Increases 5 Mile HHI	(0.0912)	(0.139)	(0.115)	(0.00502)	(0.00570)	(0.0163)	(0.0151)	(0.00903)	(0.00315)	(0.00110)	(0.000489)
Observations	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Dep. Var. Mean	7.538	1.337	0.589	2.449	0.095	0.382	0.523	0.881	0.141	0.030	0.007
Units	log(IU)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. HHI is facility specific. Each facility denotes a separate market made up of facilities within 5 miles of that facility. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 23: Acquisition Effects For HHI Increases - 10 Mile Radius Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1) Epo	(2) Venofer	(3) Ferrlecit	(4) HGB	(5) HGB Good	(6) HGB Low	(7) HGB High	(8) URR Good	(9) Any Cause	(10) Sept.	(11) Cardiac Event
Post-Acquisition	0.784***	0.537***	-0.245**	0.00656	-0.0104*	0.0303**	-0.0199*	0.0118	0.00392	0.000214	0.000501
	(0.0794)	(0.109)	(0.0907)	(0.00473)	(0.00506)	(0.00997)	(0.00995)	(0.00615)	(0.00268)	(0.000933)	(0.000448)
Post-Acquisition ×	-0.0159	0.112	-0.0872	0.00514	-0.00180	0.0120	-0.0102	0.00991	0.00314	0.000612	0.000362
Increases 10 Mile HHI	(0.0841)	(0.142)	(0.118)	(0.00544)	(0.00599)	(0.0151)	(0.0145)	(0.00842)	(0.00330)	(0.00115)	(0.000521)
Observations	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Dep. Var. Mean	7.538	1.337	0.589	2.449	0.095	0.382	0.523	0.881	0.141	0.030	0.007
Units	log(IU)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. HHI is facility specific. Each facility denotes a separate market made up of facilities within 10 miles of that facility. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 24: Acquisition Effects By Potential Competitors Within 1 Mile

	Drugs			Clinical Outcomes					Hospitalized		
	(1) Epo	(2) Venofer	(3) Ferrlecit	(4) HGB	(5) HGB Good	(6) HGB Low	(7) HGB High	(8) URR Good	(9) Any Cause	(10) Sept.	(11) Cardiac Event
Post-Acquisition	0.796***	0.683***	-0.351***	0.00935**	-0.00986***	0.0400***	-0.0301**	0.0131*	0.00712***	0.00139*	0.000679*
	(0.0741)	(0.0809)	(0.0691)	(0.00287)	(0.00298)	(0.0103)	(0.00932)	(0.00521)	(0.00183)	(0.000617)	(0.000300)
Post-Acquisition ×	-0.0536	-0.195*	0.130	0.00161	-0.00490	-0.00517	0.0101	0.0148*	-0.00320	-0.00219*	0.000189
Has Competitor Within 1 Mile	(0.0671)	(0.0902)	(0.0764)	(0.00323)	(0.00384)	(0.0116)	(0.0107)	(0.00663)	(0.00262)	(0.000881)	(0.000374)
Post-Acquisition	0.795***	0.688***	-0.354***	0.00951***	-0.00992***	0.0403***	-0.0304**	0.0132*	0.00705***	0.00132*	0.000689*
	(0.0742)	(0.0809)	(0.0691)	(0.00287)	(0.00300)	(0.0103)	(0.00935)	(0.00522)	(0.00182)	(0.000616)	(0.000300)
Post-Acquisition ×	-0.0372	-0.149	0.0826	0.00221	-0.00501	-0.00267	0.00768	0.0163*	-0.00335	-0.00270**	0.000152
1 Competitor Within 1 Mile	(0.0702)	(0.0964)	(0.0779)	(0.00334)	(0.00420)	(0.0114)	(0.0105)	(0.00680)	(0.00245)	(0.000931)	(0.000387)
Post-Acquisition ×	-0.142	-0.297*	0.273*	0.00319	-0.00609	-0.00744	0.0135	0.00926	-0.00430	-0.00185	0.000633
2 Competitors Within 1 Mile	(0.0951)	(0.118)	(0.106)	(0.00465)	(0.00561)	(0.0207)	(0.0194)	(0.0101)	(0.00432)	(0.00107)	(0.000541)
Post-Acquisition ×	-0.00800	-0.587*	0.378	-0.00884	-0.000785	-0.0272	0.0280	0.0126	0.00115	0.00242	-0.000526
3+ Competitors Within 1 Mile	(0.245)	(0.292)	(0.204)	(0.0110)	(0.00968)	(0.0238)	(0.0178)	(0.0196)	(0.0112)	(0.00268)	(0.00130)
Patient-Months	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Units	log(UI)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Pat. & Fac Controls	X	X	X	X	X	X	X	X	X	X	X
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Each panel represents a separate specification. The top panel includes a dummy variable for having a competing facility within 1 mile. Potential competitors are defined as facilities owned by a different firm within 1 mile in the current time period. The bottom panel includes dummy variables for the number of competing facilities within 1 mile. Observations may vary due to availability of ZIP Code geocoding data. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 25: Acquisition Effects By Potential Competitors Within 5 Miles

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.788***	0.631***	-0.284***	0.00717**	-0.00970**	0.0237**	-0.0140	0.0156**	0.00470*	0.000967	0.000349
	(0.0810)	(0.0882)	(0.0759)	(0.00270)	(0.00334)	(0.00833)	(0.00794)	(0.00564)	(0.00201)	(0.000736)	(0.000363)
Post-Acquisition ×	-0.0170	-0.0289	-0.0297	0.00427	-0.00291	0.0225*	-0.0196	0.00420	0.00200	-0.000545	0.000616
Has Competitor Within 5 Miles	(0.0646)	(0.0931)	(0.0803)	(0.00288)	(0.00341)	(0.0110)	(0.0103)	(0.00627)	(0.00233)	(0.000850)	(0.000381)
Post-Acquisition	0.804***	0.686***	-0.319***	0.00762**	-0.0102**	0.0253**	-0.0151	0.0156**	0.00449*	0.000894	0.000355
	(0.0810)	(0.0899)	(0.0775)	(0.00378)	(0.00349)	(0.00885)	(0.00843)	(0.00573)	(0.00204)	(0.000743)	(0.000368)
Post-Acquisition ×	0.0602	0.195	-0.172	0.00628	-0.00568	0.0288	-0.0231	0.00463	0.000817	-0.000940	0.000618
1 Competitor Within 5 Miles	(0.0760)	(0.103)	(0.0911)	(0.00378)	(0.00392)	(0.0155)	(0.0141)	(0.00669)	(0.00272)	(0.00102)	(0.000427)
Post-Acquisition ×	-0.0338	-0.106	-0.0437	0.00646	0.00129	0.0492**	-0.0505**	-0.00723	0.00507	0.000181	0.00103
2 Competitors Within 5 Miles	(0.0744)	(0.133)	(0.117)	(0.00389)	(0.00510)	(0.0165)	(0.0161)	(0.00941)	(0.00344)	(0.00119)	(0.000585)
Post-Acquisition ×	-0.107	-0.341**	0.178	0.000982	-0.000880	0.00547	-0.00459	0.00769	0.00240	-0.000309	0.000468
3+ Competitors Within 5 Miles	(0.0824)	(0.112)	(0.0960)	(0.00412)	(0.00491)	(0.0129)	(0.0119)	(0.00860)	(0.00314)	(0.00109)	(0.000456)
Patient-Months	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Units	log(UI)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Pat. & Fac Controls	X	X	X	X	X	X	X	X	X	X	X
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Each panel represents a separate specification. The top panel includes a dummy variable for having a competing facility within 5 miles. Potential competitors are defined as facilities owned by a different firm within 5 miles in the current time period. The bottom panel includes dummy variables for the number of competing facilities within 5 miles. Observations may vary due to availability of ZIP Code geocoding data. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 26: Acquisition Effects By Potential Competitors Within 10 Miles

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.797***	0.616***	-0.247**	0.00763**	-0.00973**	0.0245**	-0.0147*	0.0169**	0.00338	0.000665	0.0000835
	(0.0883)	(0.0919)	(0.0805)	(0.00281)	(0.00356)	(0.00808)	(0.00750)	(0.00548)	(0.00224)	(0.000855)	(0.000413)
Post-Acquisition ×	-0.0270	-0.00473	-0.0760	0.00315	-0.00253	0.0188	-0.0163	0.00203	0.00358	-0.0000670	0.000908*
Has Competitor Within 10 Miles	(0.0723)	(0.0997)	(0.0852)	(0.00280)	(0.00351)	(0.0104)	(0.00971)	(0.00620)	(0.00242)	(0.000930)	(0.000422)
Post-Acquisition	0.815***	0.668***	-0.278***	0.00801**	-0.00966*	0.0261**	-0.0164*	0.0160**	0.00341	0.000650	0.000122
	(0.0879)	(0.0936)	(0.0829)	(0.00310)	(0.00377)	(0.00893)	(0.00834)	(0.00559)	(0.00230)	(0.000863)	(0.000422)
Post-Acquisition ×	0.0536	0.208	-0.202*	0.00503	-0.00205	0.0266	-0.0245	-0.00234	0.00390	-0.000134	0.00110*
1 Competitor Within 10 Miles	(0.0890)	(0.113)	(0.0989)	(0.00426)	(0.00416)	(0.0172)	(0.0157)	(0.00702)	(0.00278)	(0.00105)	(0.000498)
Post-Acquisition ×	0.0372	-0.259	0.0577	0.00113	-0.00462	0.0148	-0.0101	0.00352	0.00133	-0.000144	0.000830
2 Competitors Within 10 Miles	(0.0929)	(0.152)	(0.128)	(0.00346)	(0.00544)	(0.0156)	(0.0156)	(0.0106)	(0.00369)	(0.00131)	(0.000595)
Post-Acquisition ×	-0.105	-0.163	0.0183	0.00194	-0.00254	0.0130	-0.0105	0.00534	0.00373	0.00000206	0.000769
3+ Competitors Within 10 Miles	(0.0832)	(0.122)	(0.103)	(0.00393)	(0.00488)	(0.0125)	(0.0115)	(0.00780)	(0.00306)	(0.00113)	(0.000486)
Patient-Months	14,161,244	11,595,400	12,473,162	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244	14,161,244
Units	log(UI)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Pat. & Fac Controls	X	X	X	X	X	X	X	X	X	X	X
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Each panel represents a separate specification. The top panel includes a dummy variable for having a competing facility within 10 miles. Potential competitors are defined as facilities owned by a different firm within 10 miles in the current time period. The bottom panel includes dummy variables for the number of competing facilities within 10 miles. Observations may vary due to availability of ZIP Code geocoding data. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

The results above show that the effect of an acquisition on, say, how much EPO a provider gives its patients is not influenced by whether or how much the acquisition increased HHI, which suggests that the transference of firm strategy does not depend on market structure. In addition, perhaps the cleanest test of this involves monopoly markets. About 1/3 of all acquisitions happen in monopoly markets, where there is no change in market structure by definition (i.e., there is just one facility in the market before and after an acquisition). As the results in Table 27 show, our baseline findings hold even when we restrict ourselves to just using these markets.

We also conside those markets (defined as HSAs) that are not "worrisome" according to the 2010 Horizontal Merger Guidelines. That is, we look only at acquisitions with a change in HHI < 100 or where the market is un-concentrated (HHI $<$1500). As we have mentioned before, most of the markets in which acquisitions occur do not experience a change in market structure because acquisitions represent de novo entry by the acquiring firm, and in those where HHI grows due to the acquisition, things were already fairly competitive. Thus, most of the identifying variation in our baseline results stems from markets that the DOJ and FTC would not classify as "worrisome." A related point is made by Wollmann (2018). The results when we restrict ourselves to looking only at these markets appear in Table 28. As the table shows, the results are very similar to our baseline results.

Table 27: Acquisition Effects in HSAs With 1 Facility

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	URR Good	HGB	HGB Good	HGB Low	HGB High	Any Cause	Sept.	Cardiac Event
Post-Acquisition	1.030***	0.645***	-0.374**	0.0146	0.0101*	-0.0238	-0.0145**	0.0383*	0.00826*	0.00120*	0.000677
	(0.119)	(0.155)	(0.126)	(0.00804)	(0.00486)	(0.0142)	(0.00534)	(0.0160)	(0.00323)	(0.000565)	(0.00112)
Observations	3,387,541	2,603,137	2,856,211	3,387,541	3,177,071	3,177,071	3,177,071	3,177,071	3,387,541	3,387,541	3,387,541
Dep. Var. Mean	7.392	1.319	0.594	0.881	2.451	0.524	0.092	0.385	0.138	0.007	0.030
Units	log(IU)	log(mg)	log(mg)	pp	log(g/dL)	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample and where there is only 1 facility in the HSA. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. Each panel represents a separate specification. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 28: Effect of Acquisition in "Non-Worrisome" Markets

	Drugs			Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Epo	Venofer	Ferrlecit	HGB	HGB Good	HGB Low	HGB High	URR Good	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.798***	0.563***	-0.271**	0.00999*	-0.0124*	0.0343**	-0.0219*	0.0213**	0.00769**	0.00117	0.000901*
	(0.0836)	(0.118)	(0.0943)	(0.00415)	(0.00505)	(0.0112)	(0.0103)	(0.00717)	(0.00264)	(0.000972)	(0.000379)
Observations	13,277,095	10,779,274	11,621,592	12,461,781	12,461,781	12,461,781	12,461,781	13,277,095	13,277,095	13,277,095	13,277,095
Dep. Var. Mean	7.515	1.311	0.599	2.449	0.096	0.381	0.524	0.880	0.141	0.030	0.007
Units	log(IU)	log(mg)	log(mg)	log(g/dL)	pp	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls	X	X	X	X	X	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. Acquired facilities that are deemed potentially problematic by the Horizontal Merger Guidelines are dropped. We drop observations within 6 months of the month of acquisition. Drug doses are winsorized at the 99th percentile. HHI is calculated at the HSA level. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

F Excluding Patient Characteristics

Here, we present results without patient covariates, which suggest that if selection on patient covariates is occurring, it is in favor of healthier patients and biases our results towards zero.

Table 29: Robustness Check: Acquisition Effects Excluding Patient Controls

	Drugs & Payments				Clinical Outcomes					Hospitalized		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Epo	Venofer	Ferrlecit	Payments	URR Good	HGB	HGB Good	HGB Low	HGB High	Any Cause	Sept.	Cardiac Event
Post-Acquisition	0.781***	0.582***	-0.272***	0.0670***	0.0201***	0.00876***	-0.0206*	-0.0105***	0.0312***	0.00623***	0.000694**	0.000747
	(0.0577)	(0.0727)	(0.0625)	(0.00597)	(0.00469)	(0.00256)	(0.00829)	(0.00291)	(0.00896)	(0.00165)	(0.000245)	(0.000565)
Observations	14,161,244	11,595,400	12,473,162	14,161,243	14,161,244	13,271,104	13,271,104	13,271,104	13,271,104	14,161,244	14,161,244	14,161,244
Baseline Estimate	0.829	-0.303	-0.612	0.0665	0.0183	0.00992	-0.0266	-0.0116	0.0382	0.00599	0.000746	0.000616
Units	log(IU)	log(mg)	log(mg)	log($)	pp	log(g/dL)	pp	pp	pp	pp	pp	pp
Year x Month FE	X	X	X	X	X	X	X	X	X	X	X	X
Pat. & Fac. Controls												
Facility FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a patient-month. Sample includes hemodialysis patients who have complete covariates and are treated at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop observations within 6 months of the month of acquisition. Specifications include only time and facility fixed effects as controls. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

Table 30: Robustness Check: Survival Acquisition Effects Excluding Patient Controls

	Survives for:		
	(1) 180 Days	(2) 365 Days	(3) 730 Days
Post-Acquisition	-0.00718	-0.00707	-0.00832
	(0.00368)	(0.00507)	(0.00706)
Observations	609,960	539,487	457,184
Baseline Estimate	-0.0107	-0.0127	-0.0174
Units	pp	pp	pp
Year FE	X	X	X
Pat. & Fac. Controls			
Facility FE	X	X	X

Notes: Facility-clustered standard errors in parentheses. An observation is a new dialysis patient. Sample includes new patients starting dialysis at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop any patients whose observation window overlaps the acquisition date. We only include those patients who remain at their original facility until death or the end of the observation window. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

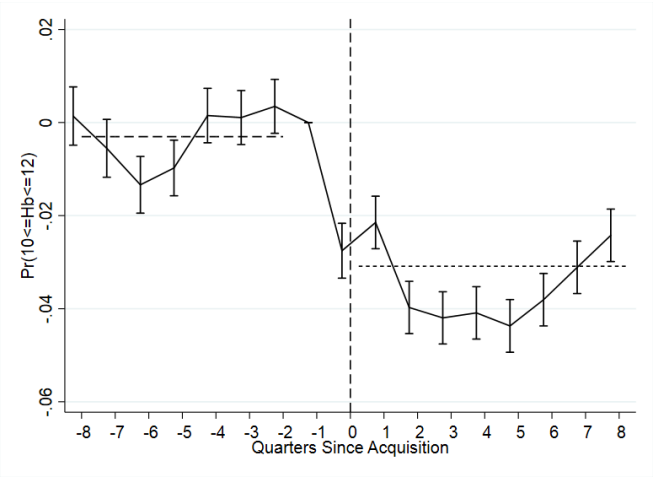
Table 31: Robustness Check: Transplant Acquisition Effects Excluding Patient Controls

	Waitlisted or Transplanted Within:		
	(1) 180 Days	(2) 365 Days	(3) 730 Days
Post-Acquisition	-0.00229	-0.00355	-0.00415
	(0.00275)	(0.00449)	(0.00785)
Observations	690,391	610,955	498,056
Baseline Estimate	-0.00568	-0.0108	-0.0188
Units	pp	pp	pp
Year FE	X	X	X
Pat. & Fac. Controls			
Facility FE	X	X	X

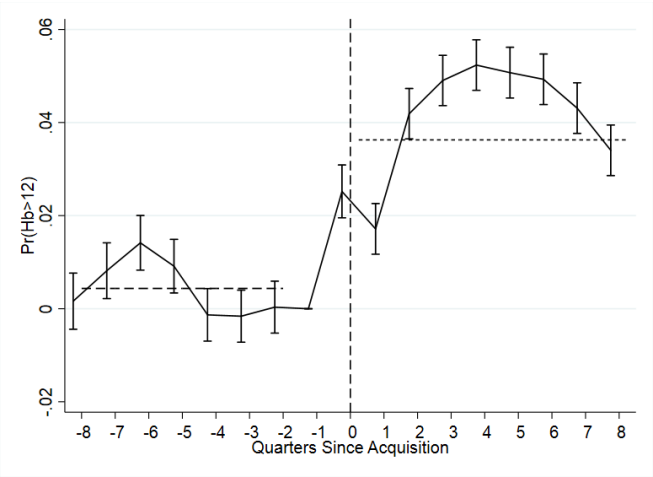
Notes: Facility-clustered standard errors in parentheses. An observation is a new dialysis patient. Sample includes new patients starting dialysis at facilities involved in an independent-to-chain acquisition or that are independent or owned by the same chain for the entirety of our sample. We drop any patients whose observation window overlaps the acquisition date. We only include those patients who remain at their original facility until death or the end of the observation window. *, ** and *** indicate significance at the 5%, 1% and 0.1% level, respectively.

G Event Studies

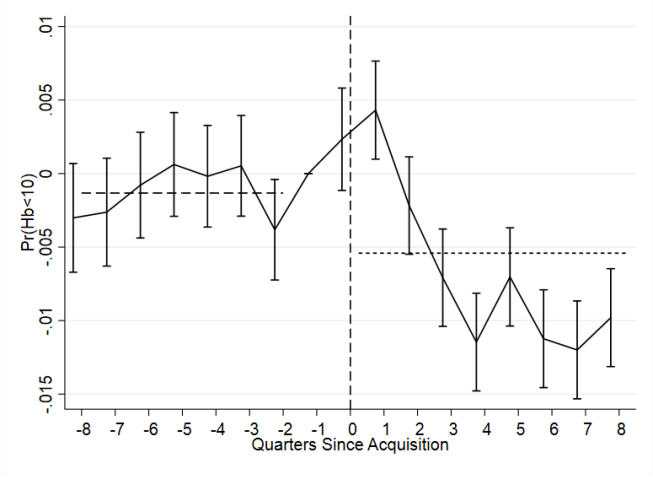
In this appendix, we present other event studies of the dependent variables analyzed in Section 4 but for which we did not include figures. For monthly plots, months outside the 48 month window are included in the regression but not shown. Observations are binned by quarter to reduce noise. Observations within 6 months of acquisition are included. Horizontal lines indicate mean of pre- and post- acquisition dummy variables, respectively. For annual plots, years outside the 8 year window are included in the regression but not shown. Error bars are 95 percent confidence intervals.



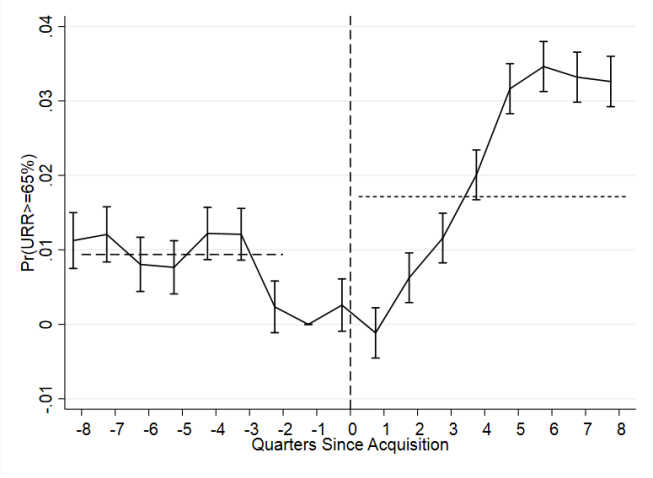
Good Hemoglobin



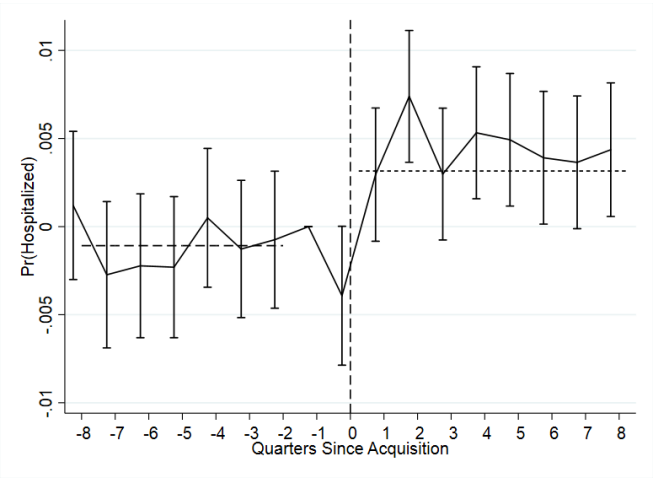
High Hemoglobin



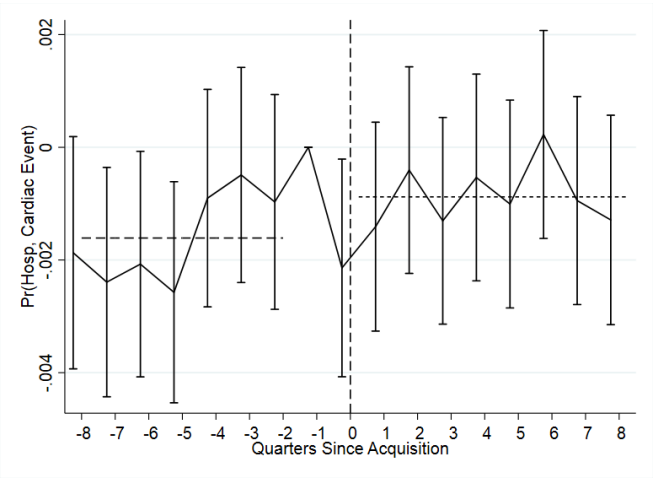
Low Hemoglobin



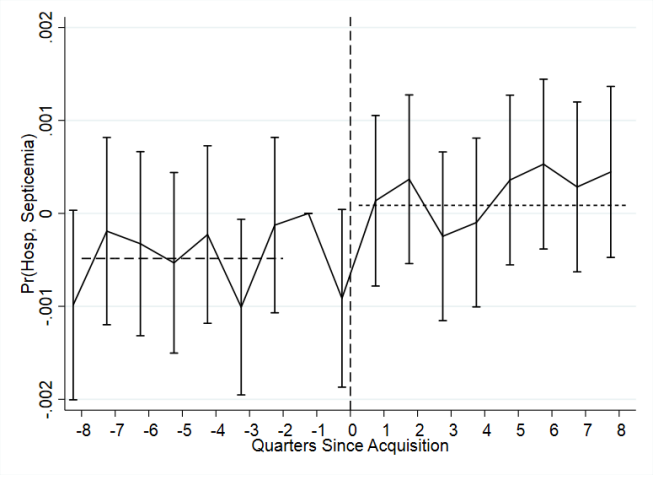
Good URR



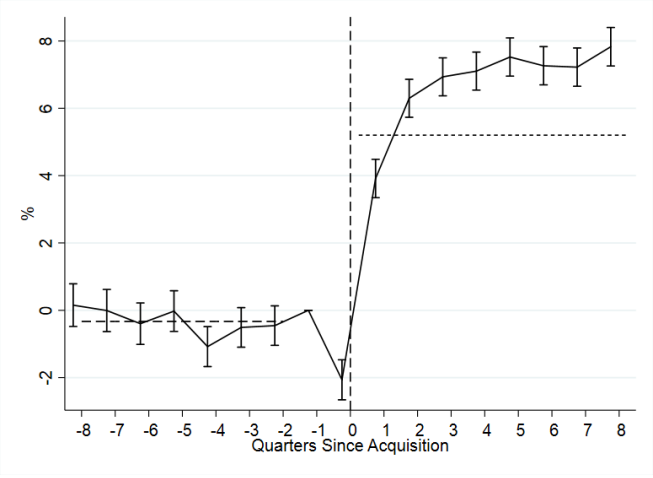
Any Cause Hospitalization



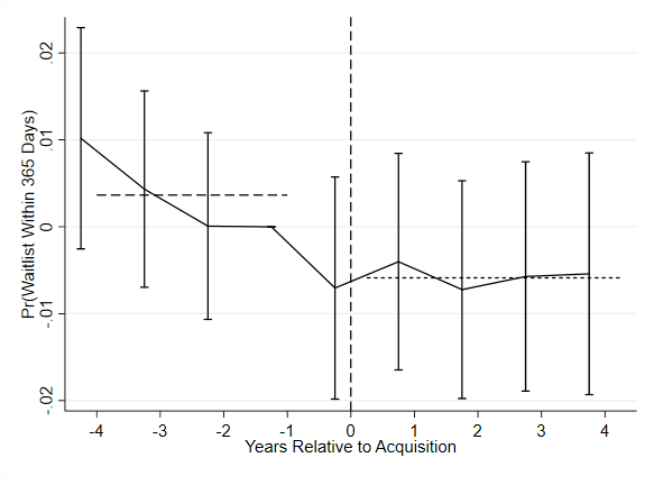
Cardiac Hospitalization



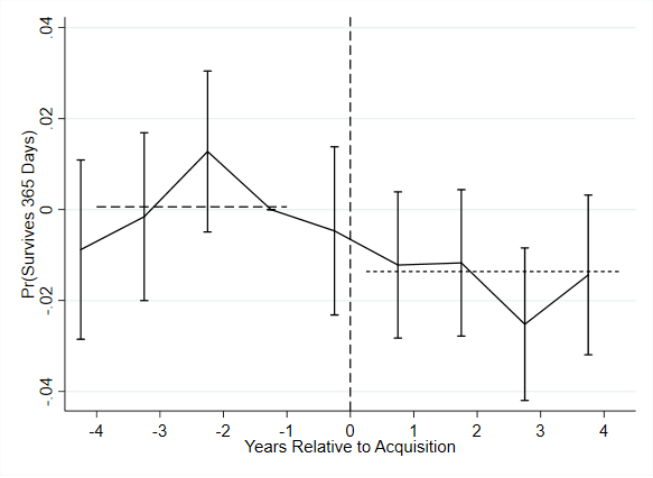
Septicemia Hospitalization



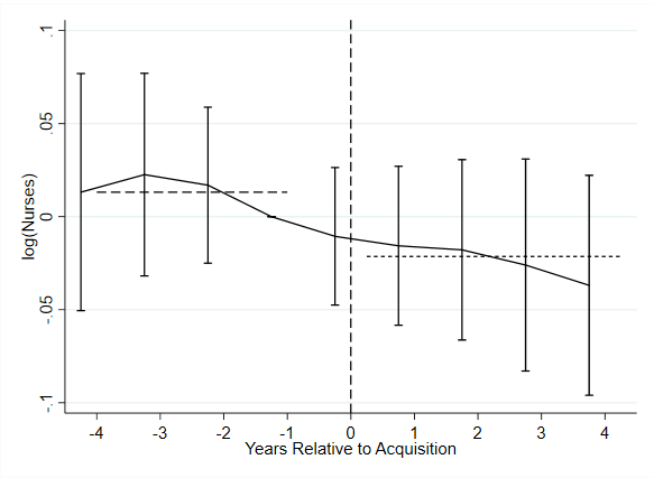
Payments



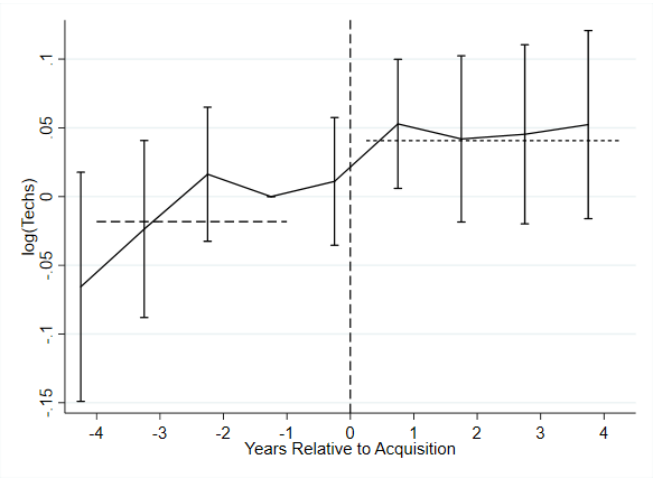
1 Year Waitlisted



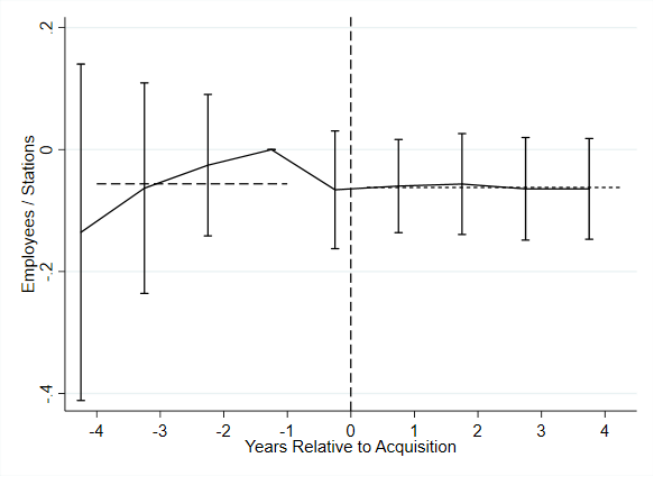
1 Year Survival



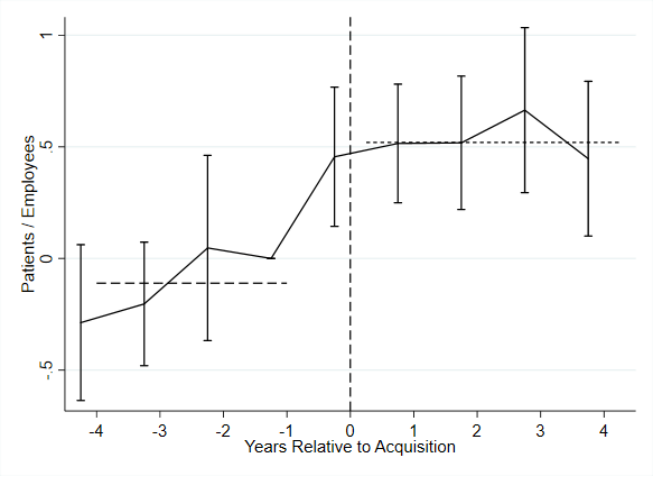
Nurses



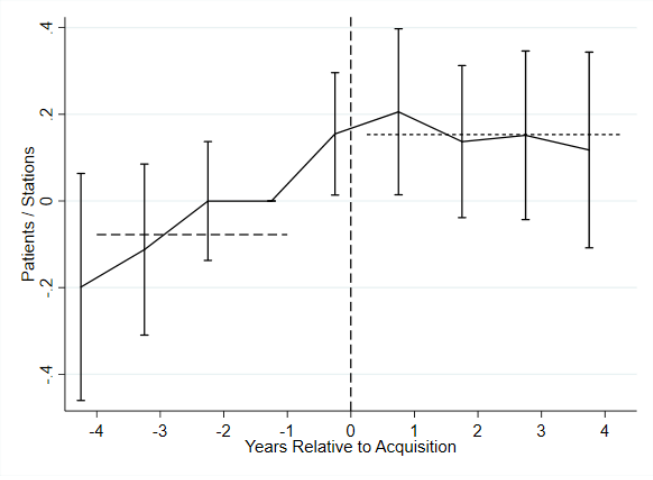
Technicians



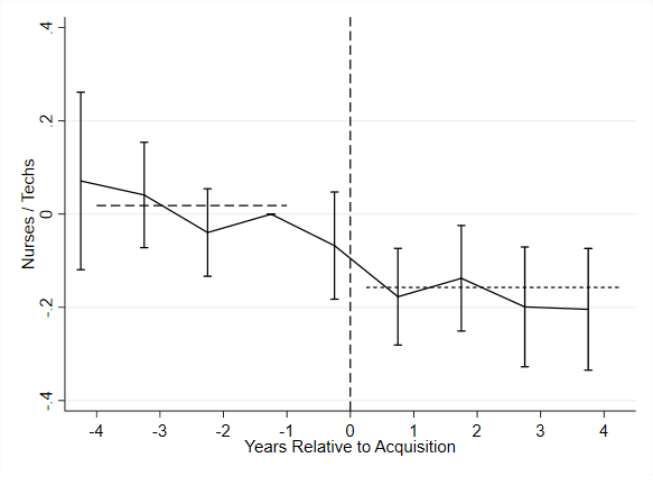
Employees-Per-Station



Patients-Per-Employee



Patients-Per-Station



Nurses-Per-Technician

H Identifying Changes of Ownership and Acquisition Dates

We construct our acquisition data in two steps. First, we identify the set of facilities that undergo an acquisition using the Annual Facility Survey from the USRDS data. These data identify the chain affiliation of each facility on an annual basis. In most cases, we can track the same facility across years using their Medicare ID and observe changes in chain affiliation. However, sometimes the Medicare ID changes after an acquisition. To identify these cases, we match facilities with the same location that have different chain affiliations in consecutive years and interpret this as a change in ownership.

Second, after identifying the set of facilities that changed ownership, we use a variety of sources, all published by CMS, to establish the precise date the change occurred. To do so, we assign each facility the acquisition date that is highest in the following hierarchy:

1. Change of Ownership date in Provider of Service File (PoS)
2. Certification date in PoS
3. Certification date in cost reports (HCRIS)
4. Report filing date in cost report if multiple reports are filed for one year.

The use of certification dates, in addition to reported change of ownership dates, is motivated by CMS documentation. Data from the PoS come from CMS registration form 855-A. This form states that certification as a new provider is required if the provider is: "Undergoing a change of ownership where the new owner will not be accepting assignment of the Medicare assets and liabilities of the seller/former owner." Additionally, filing regulations for cost reports state (CMS-Pub. 15-2-1): "A provider (including a provider that changes ownership) is considered to be a new provider upon its entry into the program if it enters the program at the inception of or during its initial business year. ... If the provider enters the program at the same time that it begins operations, the initial cost reporting period will begin with the effective date of participation."

Below, we present a table with the number of acquisition dates matched in each step. Of the 1,236 acquisitions identified in the data, we are able to match precise acquisition dates to 1,088. After restricting to facilities where we observe patients, we end up with a sample of 1,026 acquisitions.

These dates are very difficult to validate from sources outside of CMS, as acquisitions are not (usually) required to be reported to antitrust authorities. That said, we check these dates for consistency across all of our sources and find that more than 80% of acquisitions match multiple criteria and there are no instances of a facility having multiple conflicting matched dates.

Source for Acquisition Date	Count
PoS Change of Ownership Date	761
PoS Certification Date	299
HCRIS Certification Date	24
HCRIS Report Dates	4
Total Number of Acquisitions Identified in Facility Survey	1,236
Number Matched to Precise Acquisition Date	1,088

Notes: Each observation is an acquisition event. Counts in the first panel only include new matches. For example, if a facility matches both the PoS Change of Ownership date and PoS Certification date, it will be counted in the first row but not the second.

I Standardization

Table 32 shows the R^2 from estimating the regression,

$$Epo_{ijt} = \alpha_y X_{ijt} + \gamma_j + \epsilon_{ijt}, \tag{8}$$

separately for pre- and post-acquisition facilities. That is, we regress EPO on all patient covariates included in equation (1) but allow each year to have a separate coefficient.

Table 32: Standardization

	(1) Pre-Acquisition	(2) Post-Acquisition
N	1,483,917	1,960,286
R^2	0.109	0.176

Notes: An observation is a patient-month. R^2 from equation (8). Covariates included are the same as equation (1).