# THREE ESSAYS ON THE ECONOMICS OF DIALYSIS

By

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## ABSTRACT

### CHAPTER 1: QUALITY DISCLOSURE AND PATIENT SWITCHING: EVIDENCE FROM THE DIALYSIS INDUSTRY

In 2012, the Centers for Medicare & Medicaid Services (CMS) implemented the End Stage Renal Disease Quality Incentive Program (QIP) to improve information transparency between dialysis patients and their treatment center by publishing novel quality scores. How dialysis patients respond to these new scores is unclear. This paper explores the extent to which the publication of quality scores influences patients' likelihood of switching dialysis centers, and whether the salience of these scores induces a behavioral change in patients. My findings show that patients at centers with lower quality scores are significantly more likely to switch than those at high quality centers. Specifically, patients at centers with a published score in the $10^{th}$ percentile are nearly 19% (1.10 percentage points) more likely to switch than patients at centers with a published score in the $90^{th}$ percentile. Furthermore, patients who learn they are at a low-quality center when scores are published increase their likelihood of switching by over 1.18 percentage points, suggesting that patients respond to the salience of quality scores. These results show that increasing transparency around treatment quality can affect patient decision-making and improve provider-patient matching, with implications for patient welfare and resource allocation.

### CHAPTER 2: PATIENT PREFEENCE OR PROVIDER INFLUENCE: VARIATION IN HEALTH CARE SPENDING AMONG DIALYSIS PATIENTS

Dialysis patients spend a substantial amount of time interacting with the staff and peers at their dialysis center, making these environments a potentially important influence on patient behavior. In this paper, I use patient switching to disentangle the demand- and supply-side factors that influence general health care spending. Leveraging an event study design, I examine changes in non-dialysis medical spending before and after a patient switches to a new dialysis provider, relating these changes to the utilization patterns of their new peers. The results show that switchers experience an immediate and persistent change in non-dialysis spending. Point estimates suggest that dialysis centers account for between 37.6% and 61.2% of the variation in a patient's non-dialysis health

care spending. The effects are strongest in spending categories with greater patient discretion, such as non-dialysis outpatient visits, suggesting that policies aimed at reducing costs may benefit from appropriate targeting.

## CHAPTER 3: VALUE-BASED PURCHASING AND PAYMENT REDUCTIONS: DIALYSIS CENTER RESPONSE TO THE END STAGE RENAL DISEASE QUALITY INCENTIVE PROGRAM

The Centers for Medicare & Medicaid Services introduced the End Stage Renal Disease Quality Incentive Program in 2012 to improve the quality of dialysis services and reduce costs. A key feature of this program is the implementation of value-based purchasing, which reduces reimbursement to dialysis centers that perform poorly on quality metrics. This paper evaluates whether such payment penalties are effective at improving clinical quality. Using administrative data from Medicare, I compare penalized and non-penalized dialysis centers and estimate the effect of penalties on clinical quality using three empirical approaches: a two-way fixed effects difference-in-differences model, a dynamic event study, and a model allowing treatment effect heterogeneity. The results suggest that dialysis centers penalized for low quality exhibit sustained improvements in septic infections, lower mortality rates, and fewer hospitalizations. These findings support value-based purchasing as an effective tool to incentivize improvements in treatment quality.

To my wife, Jessie, for her unwavering
love and support during this journey.

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# CHAPTER 1

# QUALITY DISCLOSURE AND PATIENT SWITCHING: EVIDENCE FROM THE DIALYSIS INDUSTRY

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

## 1.1 Introduction

Information asymmetry in healthcare occurs when patients possess less information about treatment quality than their providers, a well-known problem in healthcare markets (Arrow, 1963). This information gap distorts patient decision-making, potentially reducing welfare and leading to inefficient outcomes, particularly in the context of dialysis treatment. The information disparity can be harmful when patients are poorly matched to dialysis centers and receive low quality treatment. In many healthcare settings, state governments and federal regulators have mitigated this issue by initiating information campaigns and publishing new quality measures. The Centers for Medicare & Medicaid Services (CMS) launched the End Stage Renal Disease Quality Incentive Program in 2012 to provide dialysis patients with more accessible information on dialysis treatment quality. By publishing dialysis center quality scores, CMS aims to reduce inefficiencies in patient choice, enhance market competition, and empower patients to make more informed decisions.

Research on the Quality Incentive Program (QIP) has primarily focused on supply side responses, including the marginal response of dialysis centers to quality scores (Bertuzzi et al., 2023; Kepler et al., 2024), and the effects of payment reform through the QIP (Eliason et al., 2024; Sheetz et al., 2021). Some prior works address patient outcomes (e.g. (Eliason et al., 2024; Griffin et al., 2023)), but how patients change their behavior when information about dialysis center quality is disclosed remains understudied. In this paper, I address this research gap by focusing specifically on patient switching. My estimations show that patients are responsive to the salience of quality scores and low scores increase the likelihood of a patient leaving their dialysis center. Dialysis patients are a vulnerable population with tenuous health, underscoring the importance of understanding

how the Quality Incentive Program affects patient decision-making. Decreasing the information asymmetry of dialysis quality can improve patient-provider matching and induce patients to switch away from lower quality providers, which may improve patient welfare and lead to better health outcomes.

Patients responding to new quality information in other health settings is well-supported in the literature. In the long-term care sector, publicly reported nursing home quality measures have been shown to improve patient and family decision-making (Grabowski and Town, 2011; Zhao, 2016) and shift patient demand to higher-quality nursing homes (Werner et al., 2012). The effects of quality disclosure may be larger for negative information (Ramanarayanan and Snyder, 2012) or when the new information contradicts prior beliefs (Dranove and Sfekas, 2008). Additionally, patients may be responsive to hospital ranking (Pope, 2009), reports on hospital outcomes (Avdic et al., 2019; Dranove et al., 2003; Cutler et al., 2004), and information about primary care providers (Biørn and Godager, 2010).

Whether these results extend to dialysis patients is initially ambiguous. On the one hand, dialysis treatment is a frequent occurrence with substantial effects on quality of life and life expectancy.[1] Treatment can also be physically taxing, occurring three times per week and lasting approximately four hours per session. Dialysis patients may be particularly affected by quality disclosure because of the high stakes around treatment and the frequent interactions with providers. On the other hand, information frictions such as score complexity or large search costs may dampen the responsiveness of patients (Trisolini et al., 2006). Patients may be comfortable at their current provider, and switching to a new provider will entail high transition costs to become familiar. Additionally, patients may optimize along other dimensions, such as travel distance (Wollmann, 2020).

I evaluate how dialysis patients respond to published quality scores by first considering how switching and quality are related. Do patients at low-quality dialysis centers switch at higher rates

[1]Dialysis is typically a life-long treatment. A patient can stop dialysis if they receive a kidney transplant or, in rare cases, recover kidney function. Some patients decide to stop dialysis voluntarily and begin palliative or other end-of-life care.

than those at high-quality dialysis centers, as measured by published quality scores? I show that this is indeed the case by setting up a model of patient switching that takes published quality scores, travel distance, and other characteristics as inputs into a patient's decision to switch. Importantly, this estimation is robust to controlling for other indicators of quality, suggesting that quality scores offer patients new information. My estimates show that published quality scores have an elasticity of about -0.2, where a 10% increase in published quality leads to a 2% decrease in the likelihood a patient changes dialysis centers. Similarly, patients at a dialysis center with a published quality score in the $10^{th}$ percentile are 19% (1.11 percentage points) more likely to switch than patients at a center with a score in the $90^{th}$ percentile.

I then examine whether patients respond to the salience of published quality scores. Dialysis patients likely use noisy signals of performance to form a belief about dialysis center quality prior to 2012 when performance scores are first made available. After scores are published, a patient updates their belief about quality using this new information. If their prior belief and the new information differ, a patient will change their likelihood of switching. I find that patients at low quality dialysis centers before scores are published increase their likelihood of switching by over 1.18 percentage points when they learn about the true quality of their provider. This result is robust to different specifications of low or high quality, suggesting that the change in switching probability is stable.

Understanding how dialysis patients and dialysis centers respond to quality information has relevant policy implications. Kidney failure, or end stage renal disease (ESRD), is a diagnosis that qualifies individuals for full Medicare coverage. While ESRD patients make up about 1% of all Medicare beneficiaries, their inflation-adjusted spending accounts for around 7% of all Medicare fee-for-service expenditures from 2011-2019, totaling nearly $50 billion each year (U.S. Renal Data System, 2023). On average, CMS spends $80,000 per patient with kidney failure annually, of which $40,000 is allocated directly for dialysis treatment. In comparison, CMS spends between $10,000 to $12,000 annually on all beneficiaries. Given the substantial investment in ESRD care, empowering patients to make well-informed decisions can lead to more efficient resource allocation

by reducing the flow of reimbursement to low-quality dialysis centers. As noted in Eliason et al. (2020), allocating resources to low-quality centers represents a decline in value for CMS.

From a paternalistic viewpoint, CMS has a vested interest in ensuring that patients receive high quality care due to the implications for patient welfare and health outcomes. Dialysis patients typically spend 9 to 12 hours per week receiving treatment, not including time spent traveling or waiting for treatment to begin. If patients value high-quality care, switching away from low-quality dialysis centers can be a welfare-improving decision with relatively low marginal costs. Low-quality centers pose a higher risk of costly adverse events, such as hospitalizations or infections (Eliason, 2022; Grieco and Mcdevitt, 2017). Encouraging patients to switch away from low-quality centers may reduce these risks and represents a long term cost-saving mechanism.

On the supply side, the involvement of CMS and regulated pricing induces dialysis centers to compete along non-price dimensions, such as quality, location, and amenities (Eliason, 2019; Kepler et al., 2024; Li, 2020; Ramanarayanan and Snyder, 2012). Regulated pricing places a larger emphasis on patient volume for profit maximization. When a patient switches away from a low-quality center, it poses an immediate threat to profitability. Thus, improved quality transparency can have significant spillover effects, spurring improvements in care that benefit all patients (Kepler et al., 2024).

The reaction of dialysis patients speaks broadly to the importance of information transparency. By informing patients of the quality of treatment they are receiving, CMS and other public organizations can empower patients to make more informed decisions. Hospital report cards, for example, have been shown to improve outcomes of cardiac patients (Chou et al., 2014). In the nursing home sector, there is considerable heterogeneity in quality between nursing homes nationally and even within markets (Einav et al., 2022), suggesting that patient outcomes could be dependent on which nursing home is chosen. Careful consideration needs to be taken, however, to reduce the moral hazard associated with the link between higher quality and higher reimbursement. If sicker patients will decrease metrics and result in a financial penalty, then providers may be selective in their patient roster. Bertuzzi et al. (2023) suggests that a dialysis center may engage in "cream skimming" if a

marginal patient would decrease the published quality score enough to induce a payment penalty. While hospital report cards improve the treatment of cardiac patients, as shown in Chou et al. (2014), other research suggests that report cards give physicians and hospitals incentives to avoid complex patients (Dranove et al., 2003).

This paper offers two contributions to the current literature. First, I add to a growing body of research examining the effects of quality programs on healthcare providers, many of which are administered through the Centers for Medicare & Medicaid Services. These programs address information asymmetries that can make healthcare markets inefficient. For instance, the link between poor quality and negative patient outcomes in the nursing home industry has been well documented (Hackmann, 2019; Harrington et al., 2016). CMS launched the Nursing Home Quality Initiative (NHQI) in 1998 to track quality and began a five-star program in 2008. Nursing homes are scored on various metrics, such as patient health outcomes and facility staffing levels, and scores are published on the Nursing Home Compare website. In an examination of the effect on patient demand and nursing home quality, Grabowski and Town (2011) showed a small response by patients and an improvement in facility quality when market competition is taken into consideration. Similarly, Hackmann (2019) showed that nursing home quality increased when regulatory changes were made to the reimbursement structure.

A related area of interest is hospital quality. CMS monitors and tracks hospital quality through several programs, including the Hospital Readmissions Reduction Program (McIlvennan et al., 2015). Gupta (2021) showed that hospitals penalized for high readmission rates and mortality rates respond by improving these metrics, although these effects are highly non-linear (Norton et al., 2023). Similarly, hospital report cards have been an attractive method to disseminate quality information to patients. Cutler et al. (2004) found that patient volume and hospital quality are affected by demand-side and supply-side responses to these report cards. Report cards are also associated with lower mortality rates for severely ill patients (Chou et al., 2014). However, Dranove et al. (2003) suggest that publishing report cards for hospitals and cardiac surgeons leads to providers selecting healthier patients, and can cause less healthy patients to wait longer for surgery. Pope

(2009) found that improving a hospital's US News and World Report ranking leads to an increase in patient volume and hospital revenue. I contribute to these studies by providing new evidence that there are demand-side responses to quality programs. Many prior studies primarily use provider-level data to explore outcomes. My analysis, however, uses patient-level information to explore changes in patient behavior. The granularity of my data allows me to control for rich vectors of patient characteristics and health attributes.

My second contribution is to the literature on end stage renal disease and dialysis markets. Eliason (2022) analyzed how dialysis centers respond to price regulation through quality investments, finding that higher reimbursement can improve patient survival rates after controlling for endogenous quality and market entry. Eliason et al. (2020) concluded that dialysis centers acquired by large, for-profit chains often adapt their practices to conform to the behavior of the new parent company. Such acquisitions can negatively affect outcomes, measured by increased hospitalizations and higher patient mortality rates. Likewise, Kepler et al. (2024) documented more evidence that market entry affects quality, showing that lower quality dialysis markets are attractive to new entrants which can induce an improvement in incumbent quality. However, the incentives for providing higher quality care and treating more patients are often misaligned. A dialysis center will reduce treatment quality by decreasing treatment time in order to treat more patients and increase revenue (Grieco and Mcdevitt, 2017). Bertuzzi et al. (2023) provide evidence that dialysis centers engage in 'cream skimming' to remove patients that would reduce their performance score low enough to induce a payment penalty for poor quality. Griffin et al. (2023) examined how dialysis centers react to payment penalties, finding that overall mortality may decrease, although others suggest that the effect on quality scores may be minimal (Sheetz et al., 2021).

I contribute to the end stage renal disease literature by specifically examining how patients' behavior changes in response to published quality scores. Previous studies of the QIP have analyzed provider-level data to estimate changes in patient volume (Kepler et al., 2024), or used patient-level data to examine health outcomes (Eliason et al., 2020, 2024). Eliason et al. (2020) suggest that a patient's dialysis center being acquired by a larger chain does not induce a patient to change centers,

while Bertuzzi et al. (2023) suggest that high-risk patients are more likely to switch centers when they might trigger a payment penalty due to low quality. I extend this work by linking the likelihood of switching to quality scores, providing new insights into how patients react to reported measures of quality.

The rest of the paper proceeds as follows. In section two, I provide information on the End Stage Renal Disease Quality Incentive Program and the role of the Centers for Medicare & Medicaid Services in dialysis markets. Section three introduces the data and dialysis center quality scores. In section four, I outline a conceptual framework for understanding switching behavior among patients and describe how dialysis center quality is measured. Section five presents the empirical specification and results. Section six shows how quality scores and travel distance affect a patient's choice of dialysis center, and highlights heterogeneous responses to quality scores among different patient subgroups. Section seven considers the moral hazard associated with quality scores and patient selection. Section eight concludes.

## 1.2 Dialysis, the Role of CMS, and Quality

### 1.2.1 Dialysis

The body accumulates harmful byproducts, such as urea, as a result of normal metabolic functions like the breakdown of proteins in the liver. Healthy kidneys remove these byproducts before they cause harm. When kidneys begin to lose this ability, patients are diagnosed with early stages of chronic kidney disease (CKD). Kidney function can deteriorate to a point where waste is no longer removed quickly enough for the body to properly function. When this occurs, patients are diagnosed with end-stage renal disease (ESRD) and require dialysis, a kidney transplant, or both to replace kidney function. A common sequence is for a patient to initiate dialysis, and then apply to be on the kidney transplant waitlist. Kidney transplantation is attractive as a treatment and removes the need for dialysis, but the number of eligible kidney transplant patients far exceeds the number of available kidneys (Becker and Elías, 2007; Klein et al., 2010).

Dialysis is a necessary treatment to improve quality of life and life expectancy of patients with

ESRD. There are three types of dialysis treatment. By far the most common is hemodialysis,[2] which typically occurs in a dialysis center. During a dialysis session, a patient's blood is passed through a machine that filters out the waste products and toxins generally removed by the kidneys. Each dialysis session lasts between three and four hours and occurs three times per week. Hemodialysis markets are dominated by two large chain organizations, Davita and Fresenius Medical Care (Eliason et al., 2020). These two organizations hold more than 60% of the total market share and are responsible for the rapid pace of acquisitions and mergers starting in the late 1990's (Wollmann, 2020).

The other two types of dialysis are peritoneal dialysis and home dialysis, but both types pose much higher out-of-pocket costs for patients. Peritoneal dialysis uses a different mechanism to remove waste products, and is more common for less severe cases of ESRD and for patients with full mobility. Home dialysis uses a smaller machine in the patient's home and requires a robust support network. CMS reimburses three dialysis treatments per week, but peritoneal and home dialysis require almost daily treatment, not all of which are covered by Medicare. Patients undergoing either type of treatment are under the care of a dialysis center, even though treatment does not occur at the center. In this paper, I only consider patients undergoing in-center hemodialysis and exclude those with peritoneal and home dialysis.

### 1.2.2 CMS and Medicare Reimbursement

CMS plays a crucial role in financing healthcare for patients with end-stage renal disease. The 1972 Social Security Amendments made all end-stage renal disease patients eligible for full Medicare coverage. ESRD is one of two diseases[3] to qualify a patient for full Medicare coverage without a consideration of age. End stage renal disease and dialysis treatment are expensive, with CMS reimbursing over $80,000 per ESRD patient per year for all medical expenses, with dialysis treatment accounting for approximately half of the total cost. This amount represents 7% of total

[2] In what follows, I refer to in-center hemodialysis as dialysis.

[3] Amyotrophic lateral sclerosis (ALS), commonly referred to as Lou Gehrig's disease, qualifies a patient for Medicare coverage once they are approved for Social Security and Disability Insurance. The 24-month mandatory waiting period is waived under this circumstance.

Medicare fee-for-service (FFS) spending and is six to seven times higher[4] than the spending on all beneficiaries (U.S. Renal Data System, 2023).

If a patient is previously uninsured or has public insurance, Medicare becomes the primary payer after the third month of diagnosis. Otherwise, Medicare is the secondary payer after the three-month mark and becomes the primary payer after 33 months. More than half of all patients have Medicare as their primary payer in the first year of dialysis treatment, and almost 90% of all ESRD patients have Medicare coverage through a combination of Part A, Part B, and/or Medicare Advantage. Medicare covers 80% of the cost of dialysis, with the remaining 20% being billed to the patient, although most patients have additional insurance that covers all or most of this cost. In order to receive any Medicare reimbursement, a dialysis center must be certified by CMS and maintain their certification through annual inspections and audits.

In 2008, with the passage of the Medicare Improvements for Patients and Providers Act, CMS established the End Stage Renal Disease Quality Incentive Program (QIP). Two goals of the Program are to reduce the costs associated with dialysis and improve dialysis quality. A big influence in the trend of rising costs was the judicious use of expensive, highly reimbursable[5] drugs to treat anemia (Thamer et al., 2007). To achieve the goal of lower costs, reimbursement for dialysis treatment transitioned from a composite rate with separately billable medications to a prospective payment system. Dialysis centers receive a predetermined bundled amount for all components of a dialysis session, with some adjustments for dialysis center volume, patient case-mix, and geographic differences. The reimbursement rate changes each year and typically ranges between $230 to $240 per session. With this shift in repayment, dialysis center revenue became much more dependent on patient volume and was no longer influenced by medication reimbursement.[6]

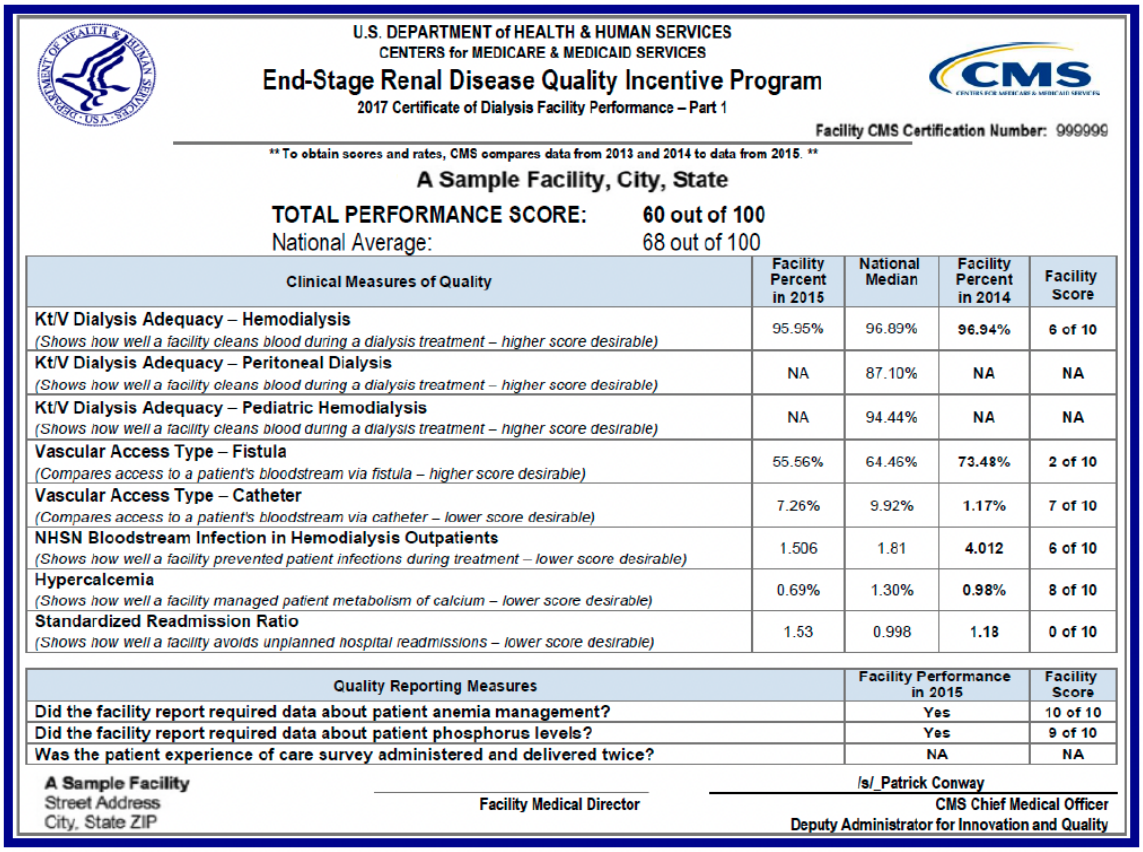
One concern about the bundled payment system is that dialysis centers will focus too much

[4]CMS spends approximately $10,000 to $12,000 on all beneficiaries.

[5]Medication used to stimulate the production of red blood cells accounted for almost 11% of ESRD reimbursement. One such drug, Epogen, cost Medicare nearly $2 billion in 2010 and was the most costly medication for Medicare Part B. (https://www.gao.gov/assets/gao-13-739t.pdf)

[6]For-profit firms were particularly affected by the payment structure change. For example, between 2001 and 2010, administering Epogen to stimulate the production of red blood cells produced between 20% and 30% *of all dialysis-related revenue* for DaVita Inc. After the first year of the prospective payment system with bundled payments, Epogen accounted for "only" 3% of revenue (DaVita, 2013).

on treatment volume at the expense of treatment quality (Grieco and Mcdevitt, 2017). If this is the case, then dialysis centers will be more reluctant to treat sicker patients (Bertuzzi et al., 2023), or they may reduce the dosage of beneficial medication (Eliason et al., 2024). To alleviate this concern specifically, and to address quality generally, CMS began measuring a comprehensive set of clinical outcomes for each dialysis center. The measures are used as inputs to generate annual performance scores. The performance scores are published on the CMS website and dialysis centers are mandated to prominently post their performance scorecard, allowing patients to view their treatment center's score. Figure 1.1 shows an example of the Performance Score Certificate (PSC) provided to each dialysis center by CMS. The layout of the PSC changes from year to year, but the information remains consistent. The total performance score, or QIP (Quality Incentive Program) score, is the published quality score of interest. Patients can see their dialysis center's score, in addition to how their provider performed relative to the national average.



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

**End-Stage Renal Disease Quality Incentive Program**

2017 Certificate of Dialysis Facility Performance – Part 1

Facility CMS Certification Number: 999999

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

**A Sample Facility, City, State**

**TOTAL PERFORMANCE SCORE: 60 out of 100**

National Average: 68 out of 100

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

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

**A Sample Facility**
Street Address
City, State ZIP

Facility Medical Director

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

Figure 1.1 Published Scorecard in 2017

Notes: This figure shows an example of the scorecard that is required to be posted by CMS. The dialysis center's total performance score is shown in bold at top. The national average is shown directly below. The dialysis center's performance in each category is outlined, in addition to the national median and the performance in the previous year.

In addition to collecting and publishing quality scores, CMS assigns a payment penalty if the QIP score falls below a certain threshold. The penalty ranges from 0.5% to 2.0%, depending on how much worse the dialysis center performed relative to a predetermined threshold, and is applied to all Medicare reimbursements for an entire payment year. When a penalized dialysis center submits a claim, Medicare subtracts the penalty amount and pays 80% of this amount with the patient being responsible for the other 20%. Dialysis centers cannot separately bill patients for the lost revenue.

### 1.2.3 Mechanisms to Affect Quality

Measuring quality, publishing quality scores, and quality-based payment reductions each provide a different mechanism to affect quality. Dialysis centers may not fully internalize the quality of service they provide, instead focusing on objectives that are indirectly aligned (e.g. mission statements) or potentially misaligned (e.g. profit maximization) with quality (Grieco and Mcdevitt, 2017). By measuring quality, dialysis centers can focus on specific areas to improve. For example, if the quality measure is the proportion of patients using a fistula for vascular access, which is preferred to a catheter, then dialysis centers focused on quality improvements will actively encourage patients to transition to a fistula for access. Measuring quality can also induce dialysis centers to focus on outcomes desired by CMS. Reaves and Weiner (2021) showed that measures added in 2017 are improved in subsequent years, but Sheetz et al. (2021) suggested that the rapid inclusion and removal of measures complicates a direct comparison. Nevertheless, emphasizing a specific quality measure may prompt dialysis centers to focus on improving that measure.

Publishing quality scores can influence both patient and provider behavior. First, dialysis patients that become aware of their dialysis center's performance score may change their behavior and switch to a different center if the revealed quality is below the preference of the patient, which is explored in the following sections. Second, rival dialysis centers and potential entrants may use quality scores as a proxy for profitability (Kepler et al., 2024). Implementing a prospective-payment system shifts the profit incentive from treatment intensity to treatment volume. If dialysis patients at low-quality dialysis centers are responsive to quality, then a new entrant in a low-quality dialysis market may entice patients to change their provider, or existing dialysis centers can increase their market share by improving their own quality. Kepler et al. (2024) suggested that new entrants seek out lower quality dialysis markets, and physicians reduce the number of referrals to a dialysis center when their quality score is low.

Performance-based payments, also known as value-based purchasing, penalize poorly performing dialysis centers and can induce changes in quality if dialysis centers are profit maximizing entities. For-profit dialysis centers have proliferated over the past few decades (Eliason et al., 2020).

Davita and Fresenius are two large, for-profit dialysis firms[7] that together hold over 60% of the dialysis market share. For-profit dialysis firms account for almost 90% of all outpatient dialysis centers (U.S. Renal Data System, 2023). Under value-based purchasing, dialysis centers scoring below a threshold are assessed a payment penalty. While the percentage is small, between 0.5% and 2.0%, this reduction represents a non-trivial amount of revenue. Suppose a dialysis center has a patient roster consisting of 100 patients, 80 of whom have Medicare as their primary insurer. Dialysis patients receive treatment three times per week and Medicare reimburses $240 for each treatment. Without a payment penalty, the revenue generated by Medicare beneficiaries is close to $3,000,000.[8] A 1% payment penalty reduces revenue by about $30,000. Dialysis centers responsive to this reduction may invest resources to improve their score enough to not receive a payment penalty and ultimately improve quality. However, Sheetz et al. (2021) finds that this is not the case for dialysis centers receiving a payment penalty in 2017 and 2018, but note that the study is limited in scope.

Quality scores through the Quality Incentive Program are novel, but CMS has previously tried to promote quality and inform patients of dialysis center performance. Since 2001, dialysis center metrics have been published through the Dialysis Facility Compare (DFC) website, an online portal where patients can retrieve dialysis center information. One published metric is the risk-adjusted patient survival rate, averaged over the previous four years. Dialysis center survival rates are scored as *worse than expected*, *as expected*, or *better than expected*, depending on how their observed mortality rate compares to the expected mortality rate. While survival rates do capture an important component of dialysis center quality, they are incomplete and omit other relevant information. Additionally, this information has been shown to be difficult for patients and their families to interpret (Trisolini et al., 2006). The quality scores through the QIP, however, take more inputs and offer a more comprehensive picture of quality. The scores are intuitively scored[9] to give

[7] In this paper, I refer to a dialysis firm as the company overseeing specific dialysis treatment facilities, such as Davita and Fresenius Medical Care. A dialysis center is an individual location or a physical building where a patient receives treatment.

[8] The dialysis center receives about $37,400 per patient per year.

[9] In 2012 and 2013, the scores are out of 30. Starting in 2014, the scores are rescaled to be out of 100.

a familiar benchmark for interpretation, although they do not provide an explicit ranking of dialysis centers.

Quality scores are considered a view of overall quality, rather than an indication of performance in one measure. Dialysis center quality scores use several weighted inputs to arrive at a composite score, as shown in Table 1.1. The inputs fall into three domains: clinical, reporting, and safety. Each input is weighted within a domain, and each domain is weighted for the final score. The measures in the clinical domain are primarily outcomes from dialysis sessions, except for the arteriovenous (AV) fistula and catheter components, which are methods of vascular access. Most clinical measures are the proportion of patients that meet that measure, on average, during a calendar year. A larger number (+) indicates higher quality for some measures, while a smaller number (-) indicates higher quality for other measures. Measures in the reporting domain require a dialysis center to complete and submit a particular report. Reporting measures are attestations that a dialysis center performed a task, such as monitoring each Medicare patient's mineral metabolism or submitting dialysis event reports, for either a specific number of months (mineral metabolism, anemia management) or a certain number of times during the year (patient experience survey). In 2019, CMS shifted adverse event reporting[10] and infections to a new safety domain to emphasize their importance. Definitions for each input are presented in the Appendix A.1.

[10]The National Healthcare Safety Network (NHSN) event reporting requires dialysis facilities to report all adverse events to CMS, such as positive blood cultures and infections. The infection measure is the sum of lab-confirmed blood stream infections after one day of hospital admission.

Table 1.1 Measures Added and Removed Each Year

| **Payment Year** | | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|---|---|---|---|
| **Clinical** | | | | | | | | | |
| Hemoglobin >12 g/dL | + | | | | | | | | |
| Hemoglobin <10 g/dL | - | | | | | | | | |
| Urea Reduction Ratio (URR) | + | | | | | | | | |
| AV Fistula | + | | | | | | | | |
| Catheter > 90 days | - | | | | | | | | |
| Kt/V Dialysis Adequacy | + | | | | | | | | |
| Hypercalcemia | - | | | | | | | | |
| Infections | - | | | | | | | | |
| Standardized Readmission Ratio | - | | | | | | | | |
| Standardized Transfusion Ratio | - | | | | | | | | |
| Patient Experience Survey | + | | | | | | | | |
| **Reporting** | | | | | | | | | |
| NHSN Event Reporting | | | | | | | | | |
| Patient Experience Survey | | | | | | | | | |
| Mineral Metabolism | | | | | | | | | |
| Anemia Management | | | | | | | | | |
| Pain Assessment | | | | | | | | | |
| Depression Screening | | | | | | | | | |
| Staff Flu Vaccination | | | | | | | | | |
| **Safety** | | | | | | | | | |
| NHSN Event Reporting | | | | | | | | | |
| Infections | - | | | | | | | | |

Notes: Measures included in quality scores are indicated with a green box. Measures that are not yet added or are removed are indicated with a gray box. The three domains included in the scores are "Clinical" which measures patient outcomes and lab values, "Reporting" which indicates whether a dialysis center submitted the appropriate forms to CMS, and "Safety" which combines two infection measures to emphasize their importance. Most years see the addition of measures. Measures are removed if they are topped-out. Two conditions must be met for an input to be removed. First, the 75th percentile, or 25th percentile for measures where lower percentiles indicate better performance, is indistinguishable from the 90th (10th) percentile. The 75th (25th) percentile is indistinguishable if it is within two standard errors of the 90th (10th) percentile. Second, the truncated coefficient of variation (TCV) is less than or equal to 0.10. The TCV is calculated by first removing the lower and upper 5th percentiles and then dividing the standard deviation by the mean of this truncated distribution.

The first two years of the program used only a few measures from the clinical category, and were scored out of 30. Starting in 2014, more measures were added as inputs and the scores were adjusted to be out of 100. As shown in Figure 1.2, scores are trending downward, but this is a mechanical decrease due to the inclusion of additional inputs. Generating scores involves several

steps and takes about two years from collection to publication, so quality scores that are published in year *t* reflect quality from year *t-2*. I provide more detail on calculating scores in the Appendix A.2.

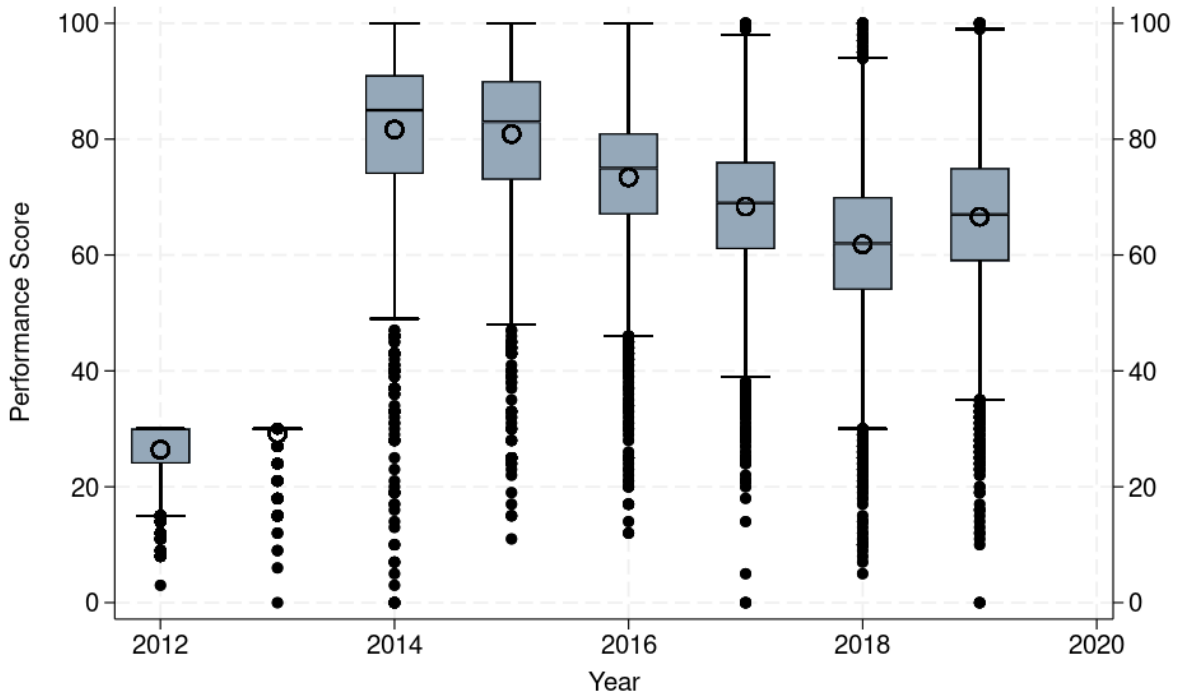



Figure 1.2 Annual Performance Score Distribution
Notes: The center circle is the average quality score. The box indicates the 75th percentile (top), 50th percentile (middle) and 25th percentile (bottom) of quality scores.

### 1.3 Data and Sample Selection

The end stage renal disease environment has several attractive features for research, two of which are particularly relevant to this study. First, most patients have detailed, comprehensive clinical information collected through their Medicare claims. Outpatient dialysis is reimbursed through Medicare Part B, providing a record of each dialysis session. This granularity is advantageous when considering patient level outcomes, such as switching dialysis centers. Second, dialysis centers are mandated to submit additional information about individual patients, aggregated clinical outcomes, and facility characteristics, which add heterogeneity between and within dialysis centers.

The main data for this paper comes from the United States Renal Data System (USRDS),

which aggregates ESRD data from various sources for each patient over time (U.S. Renal Data System, 2023). The USRDS makes available a dataset with the universe of ESRD patients in the United States. Each patients' Medicare claims, treatment histories including assigned dialysis center, demographics and health information are collected. Although the USRDS only collects Medicare claims, time periods where a patient has private insurance are still included. The data also includes annual dialysis facility characteristics, which I link with quality scores from CMS. My sample consists of all in-center dialysis patients over the age of 18 with more than one year of dialysis treatment. Patients using peritoneal or home dialysis are excluded from the sample, as are patient claims for in-hospital dialysis sessions.

The key variable of interest is whether a patient switches dialysis centers. While CMS does not collect data on why a dialysis patient leaves their dialysis center, some reasons include dissatisfaction with treatment quality, changes in preferences, a desire to reduce travel distance, or relocation (Grieco and Mcdevitt, 2017; Eliason, 2022). The barriers to switching are largely dependent on insurance coverage; for instance, a patient's private insurance plan may not be accepted at all dialysis centers, or the plan may require a physician's referral before covering a new dialysis center. However, these insurance limitations are generally trivial for Medicare beneficiaries.

To identify switches in the data, and to avoid classifying an idiosyncratic switch as a true switch, I first assign patients to their primary dialysis center by identifying their modal dialysis center in each quarter-year.[11] A patient must receive treatment at the same provider for at least two consecutive quarters. If the patient's modal dialysis center changes and remains the same for at least three consecutive quarters, I consider this to be a switch. This approach avoids capturing temporary dialysis center changes, such as patients trying out a new dialysis center but returning shortly thereafter. Furthermore, patients who travel across the country for less than half of the year and use a different dialysis center are not considered switchers. The data are then aggregated to the patient-year level, and each patient is assigned to their annual modal dialysis center. The unconditional sample rate of switching is 6.45%. This approach is similar to Bertuzzi et al. (2023),

[11] In the event of a tie, I assign patients to the first dialysis center.

and produces a similar switching rate when performed at the monthly level. I show graphically the annual switching rate in Figure 1.3, which includes a fitted quadratic line. Overall, there is a downward trend in switching but an absence of a systematic change in 2012.

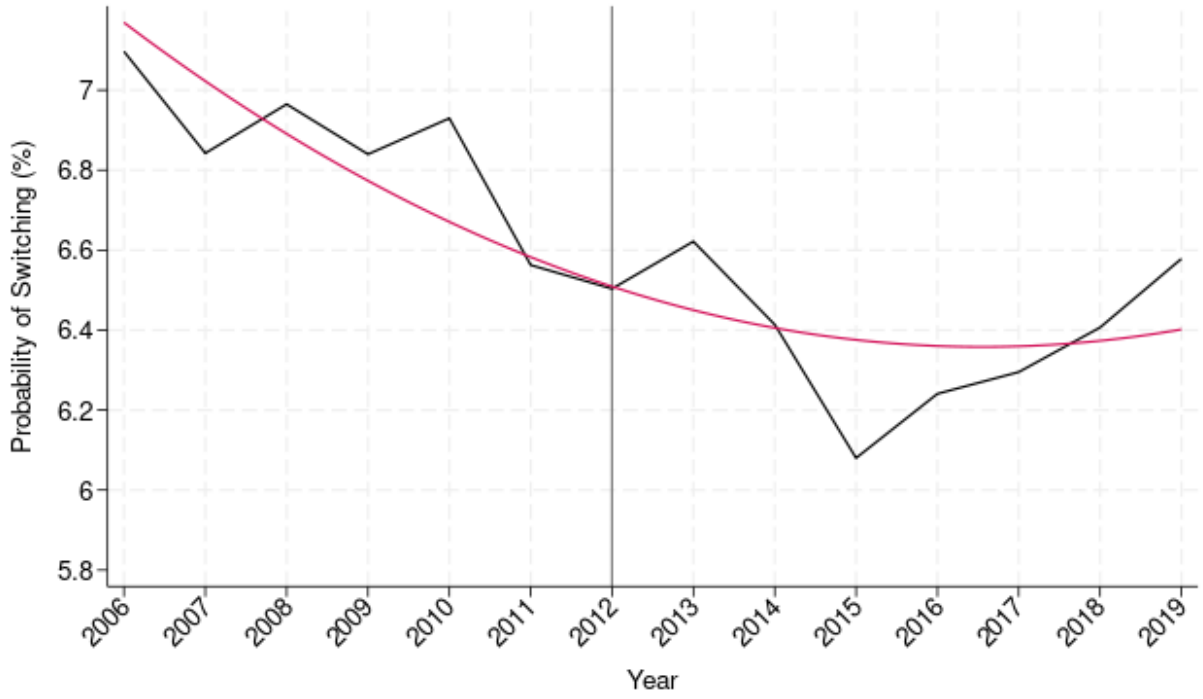



Figure 1.3 Annual Likelihood of Switching

Notes: Annual likelihood of switching is represented by the black line. A quadratic fit is also shown. The likelihood of switching is generally decreasing and does not show any jumps around 2012 and scores are first disclosed. There is an upward trend starting in 2016 that persists to 2019.

Summary statistics are shown in Table 1.2. Patient demographics are in Panel 1.2a, which includes both Medicare and non-Medicare patients.[12] Panel 1.2b details patient health characteristics, and omits years in which a patient does not have any Medicare coverage, as clinical outcomes, except for mortality, are derived from Medicare claims and are missing during these periods.

My sample consists of nearly 4.8 million total patient-years, or about 3 million Medicare patient-years, and about 1.37 million unique patients. As shown in Panel 1.2a, patients are near the Medicare eligibility age. About 56% of the sample are male, and 57% of patients are white, with Black patients accounting for about 37% of the total. Patients spend an average 4.58 years

[12]The same table excluding non-Medicare beneficiaries is very similar.

undergoing dialysis treatment. Most dialysis patients do not work when they begin treatment, and over 25% have Medicaid coverage. Primary payer information is summarized in the last four rows of the table, and many patients have additional coverage, such as private insurance or Medicare Advantage, that act as a secondary payer. The "other insurance" category includes the patient waiting period for Medicare coverage, and those with unknown insurance or no insurance.

Panel 1.2b reveals a high incidence of health complications among dialysis patients. Over 26% of patients have congestive heart failure, compared to 8% of the total population over the age of 65 (Bozkurt et al., 2023). A significant portion of dialysis patients have high blood pressure, which is the second most common cause of kidney failure after diabetes. Most patients were under the care of a nephrologist for at least six months prior to starting dialysis treatment.[13] The dialysis adequacy measure reflects the proportion of dialysis sessions with a urea reduction ratio[14] of at least 65%, while the infection rate tracks laboratory confirmed infections following at least one day in the hospital.

[13] Since patients can be chronically non-compliant with appointments or in some cases rapidly develop end stage renal disease, this number does not equal 100%.

[14] The urea reduction ratio, or URR, is a measure of how much urea is removed from the blood during the course of dialysis treatment, relative to the amount of urea in the blood prior to treatment. A higher URR is indicative of higher treatment quality.

Table 1.2 Patient Summary Statistics

(a) Patient Demographics

| % of Sample | Mean | S.D. |
|---|---|---|
| **Demographics** | | |
| Age (Years) | 62.84 | (14.82) |
| Male | 55.99 | (49.64) |
| White, Non-Hispanic | 39.33 | (48.85) |
| White, Hispanic | 17.45 | (37.95) |
| Black | 37.22 | (48.34) |
| Asian | 4.08 | (19.78) |
| Other Race | 2.93 | (16.86) |
| Years on Dialysis | 4.58 | (4.48) |
| Travel Distance* (Miles) | 3.77 | |
| Employed at Dialysis Start | 12.39 | (32.95) |
| Medicaid | 28.99 | (45.37) |
| Any Medicare | 88.42 | (31.99) |
| **Primary Payer** | | |
| Traditional Medicare | 67.58 | (46.81) |
| Medicare Advantage | 15.30 | (36.00) |
| Private Insurance | 4.90 | (21.59) |
| Other Insurance | 12.22 | (32.75) |
| **Unique Patients** | 1,377,584 | |
| **Patient-Years** | 4,778,379 | |

*Median travel distance instead of mean

(b) Patient Health

| % of Sample | Mean | S.D. |
|---|---|---|
| **Comorbidities** | | |
| Congestive Heart Failure | 26.77 | (44.28) |
| COPD | 6.26 | (24.23) |
| Diabetic | 54.87 | (49.76) |
| High Blood Pressure (BP) | 90.50 | (29.31) |
| Stroke | 7.95 | (27.06) |
| Needs Assistance w/ ADL* | 7.34 | (26.08) |
| **Health Characteristics** | | |
| Has Nephrologist | 71.12 | (45.32) |
| Primary Cause: Diabetes | 46.74 | (49.89) |
| Primary Cause: High BP | 30.35 | (45.98) |
| BMI | 29.90 | (8.21) |
| **Clinical Outcomes** | | |
| Dialysis Adequacy | 94.38 | (16.24) |
| All-Cause Hospitalizations | 1.61 | (2.16) |
| Infection Rate | 12.56 | (33.14) |
| All-Cause Mortality | 13.00 | (33.00) |
| **Switch Rate** | 6.45 | (24.56) |
| **Patient-Years** | 3,032,829 | |

*Activities of daily living

Notes: Panel (a) shows patient demographics. Median travel distance is displayed instead of average. "Any medicare" indicates that the patient has Medicare coverage as either the primary or secondary payer. "Primary insurance" refers to the insurance coverage assigned for more than half the year. "Other insurance" includes patients waiting for Medicare coverage to begin, those with unknown insurance coverage, or those without insurance. Panel (b) shows patient health characteristics. COPD is chronic obstructive pulmonary disease. ADL are activities of daily living. BP is blood pressure and BMI is a patient's body mass index.

Summary statistics for dialysis centers are shown in Table 1.3. I focus on centers that provide outpatient hemodialysis treatment.[15] While I do not impose explicit restrictions on the minimum number of patients a dialysis center needs to treat, CMS requires either an 11-patient absolute minimum for privacy reasons or distorts reported data if the patient population ranges from 11 to 25 patients. Consequently, some dialysis centers do not have available data due to these restrictions and are omitted. Most providers are for-profit with the majority being owned by either Davita or Fresenius. On average, a dialysis center administers almost 10,000 treatments to 68 patients per

[15]ESRD patients undergoing peritoneal or home dialysis are still under the care of a dialysis center, but are not considered in this study.

year. Staff certification levels vary, with high certification staff including registered nurses (RNs), dietitians, and advanced care technicians, and low certification staff including licensed practical nurses (LPNs) and patient care technicians. For certain covariates, I define a market as the hospital service area (HSA).[16] I consider the sum of all dialysis centers in a market and whether a market is exposed to a new entrant. My sample consists of 9,584 unique dialysis centers and 79,119 center-years.

Table 1.3 Dialysis Center Characteristics

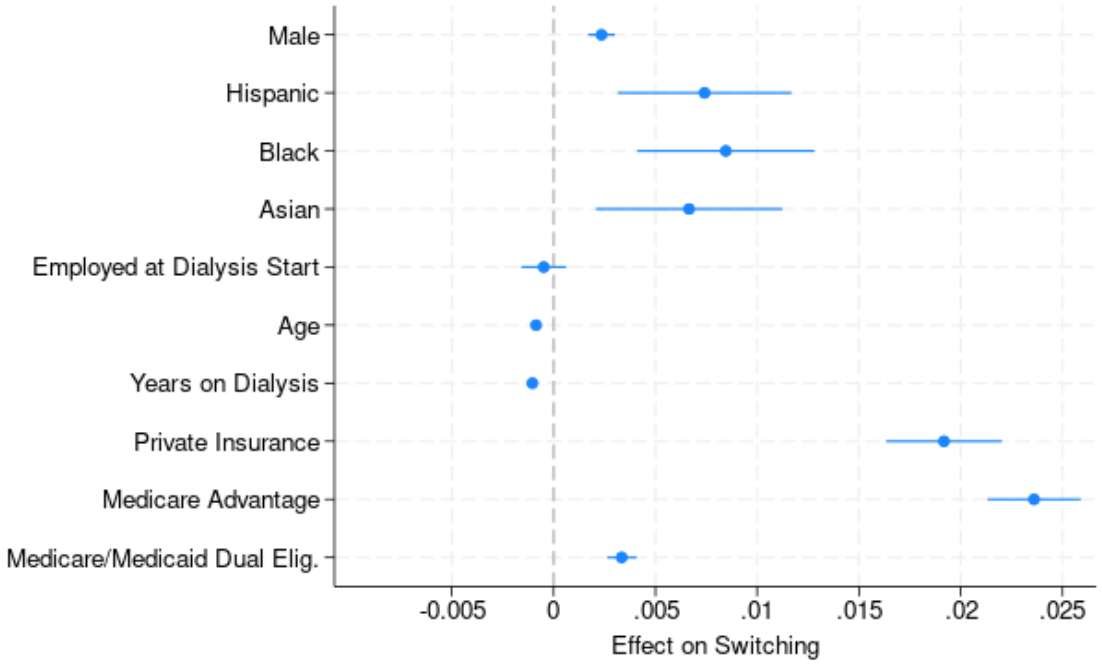
| | **Mean** | **S.D.** |
|---|---|---|
| **Provider Characteristics** | | |
| Published Quality Score (QIP) | 61.75 | (22.13) |
| For Profit (%) | 85.62 | (35.09) |
| Davita (%) | 33.03 | (47.03) |
| Fresenius (%) | 33.86 | (47.32) |
| Freestanding(%) | 92.88 | (25.72) |
| Age of Provider (Years) | 14.95 | (9.69) |
| Patients | 67.62 | (42.58) |
| Stations | 18.48 | (7.90) |
| High Certification Staff | 6.41 | (4.22) |
| Low Certification Staff | 7.18 | (5.07) |
| Competitors in Market (HSA) | 11.63 | (15.87) |
| Total Dialysis Treatments | 9,962.74 | (7,698.01) |
| **Unique Centers** | 9,584 | |
| **Center-Years** | 79,119 | |

Notes: This table presents summary statistics for dialysis centers. Davita and Fresenius are two for-profit dialysis firms. Freestanding dialysis centers are not attached to a hospital. High certification staff include registered nurses, dietitians, and advanced care tech. Low certification staff include licensed practical nurses and patient care technicians. Both high- and low-certification staff are full time equivalent, which is the number of full time staff plus half of the number of part-time staff. Markets are defined as a hospital service area.

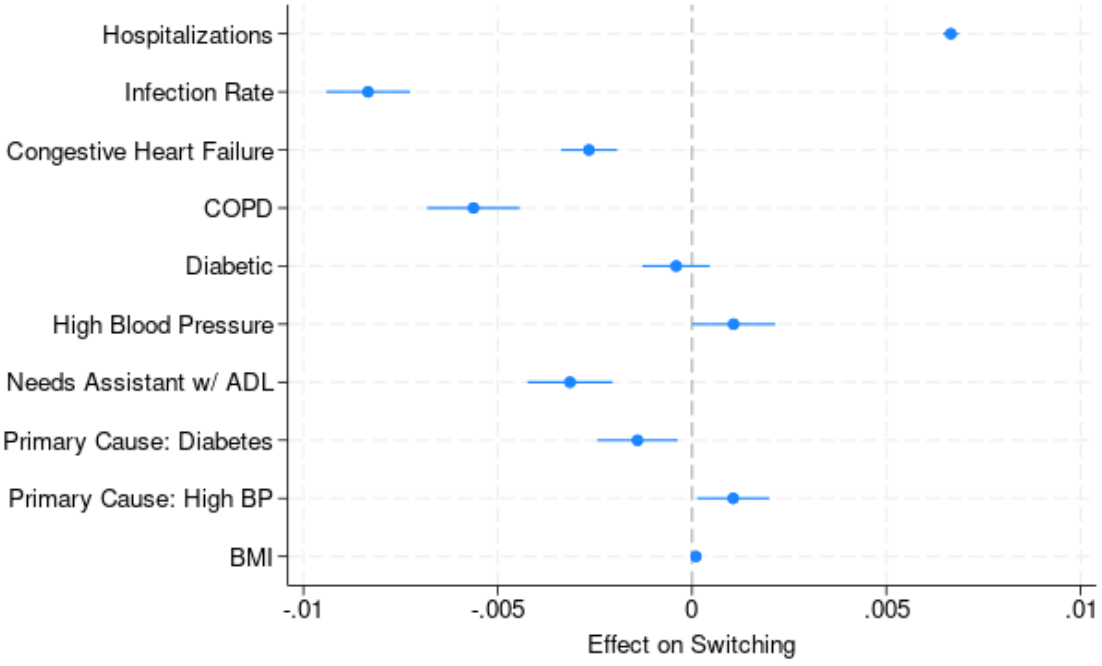
Last, I show the relationship between the likelihood of switching and patient characteristics from Table 1.2 by regressing whether a patient switches against patient characteristics. Figure

[16]HSAs are a collection of ZIP codes where a patient receives most of their inpatient care. The Dartmouth Atlas derives HSAs using Medicare claims.

1.4a shows the coefficients from patient demographics, and Figure 1.4b shows the effect of health characteristics on switching. The figures suggest that Hispanic and Black patients are more likely to switch than their non-Hispanic, non-Black counterparts. Age and employment status are negatively correlated with switching. Private insurance and Medicare advantage drastically increase a patient's likelihood of switching, relative to those that have traditional Medicare. Hospitalizations increase the likelihood of switching, which is inline with the results from Bertuzzi et al. (2023). Whether a patient has an infection is negatively correlated with switching. Other health characteristics, such as COPD, congestive heart failure, and whether a patient needs assistance with activities of daily living negatively effect the likelihood of switching.




(a) Demographics




(b) Health Characteristics

Figure 1.4 Effect of Patient Characteristics on Switching Probability

Notes: Estimated effects of patient demographics and health characteristics on the likelihood of switching. Travel distance and urbanicity are included in the estimation but omitted for scaling purposes.

## 1.4 Switching Framework and Accounting for Bias

### 1.4.1 Switching Framework

Many factors influence a patient's decision to stay or leave their current dialysis center, including quality, the patient's travel distance to their treatment center, their dialysis center's characteristics, and the patient's own idiosyncratic preferences. Switching is then influenced by a function of these four components:

$$Pr(Switch_{ijt} = 1) = f(Q_{jt}, D_{ij}, C_{jt}, X_{it}) \tag{1.1}$$

where patient $i$'s decision to stay at or switch away from dialysis center $j$ at time $t$ is a function of quality $Q_{jt}$, travel distance $D_{ij}$, provider characteristics $C_{jt}$ and patient attributes $X_{it}$. Quality is the primary focus, but is a multidimensional factor. To formalize this, define quality as:

$$Q_{jt} = f(Objective_{jt}, Subjective_{jt}) \tag{1.2}$$

Here, the overall quality $Q$ of dialysis center $j$ is a function of objective measures and subjective components. Objective quality measures are quantifiable, such as dialysis adequacy, infection rates, and mortality. After 2012, the published quality scores, $QIP_{jt}$, influence quality through the $Objective_{jt}$ quality component. In contrast, subjective quality includes factors that shape a patient's perception of quality but are difficult to measure, such as cleanliness, wait time, or staff responsiveness. Subjective quality can significantly influence a patient's switching decision. A patient may form a negative impression of a center based on subjective factors, even if objective quality is high.

It is crucial to consider both components of quality. Without accounting for subjective quality, the true effect of objective quality may be under- or over-estimated. For example, consider inputs into $QIP_{jt}$, which affects objective quality. Suppose that the input is a measure of dialysis adequacy, such as the percentage of patients with a urea reduction ratio (URR) above 65%, where a higher percentage indicates higher quality. A dialysis center can improve their URR, and therefore their $QIP$ score, by increasing treatment times. Improving objective quality by improving the URR

can affect subjective quality in various ways, and the direction of this effect depends on how the center responds to the quality-quantity trade off: serving fewer patients with higher quality or more patients with lower quality (Grieco and Mcdevitt, 2017).

A dialysis center has a few options to increase treatment time. First they can treat the same patient roster for longer. In doing so, the dialysis center can increase the treatment time but increase the time spent waiting to start treatment, or they can purchase more dialysis stations and increase the number of patients that can be treated at the same time. Second, they can choose to treat fewer patients with the same number of dialysis stations, but this decreases treatment volume and revenues. Both scenarios have different implications for subjective quality. Increasing treatment times with the same number of stations could reduce subjective quality by causing delays in treatment, while increasing capacity could improve subjective quality by reducing wait time. Failing to account for this subjective response will bias the estimated impact of objective quality.

### 1.4.2 Measuring Effort

The actions of a dialysis center influencing subject quality can be considered "effort". A dialysis center willing to put in more effort to improve a patient's experience may reduce the likelihood of a patient switching. Controlling for this effort is necessary to properly isolate the impact of objective quality on the patient's decision to switch. I use three proxy variables to account for a dialysis center's effort, with each one addressing a different mechanism that affects quality.

The first effort variable is the difference between *actual* and *predicted* dialysis stations. The number of dialysis stations is directly related to patient wait times and the duration of dialysis treatment. Longer treatment times are associated with better patient outcomes, such as higher dialysis adequacy and lower infection rates (Trisolini et al., 2006). Therefore, the difference in *actual* and *predicted* stations is an indicator for the willingness of a dialysis center to invest in additional capacity and improve outcomes and the patient's experience. For example, if a dialysis center has 60 patients on their roster and uses 20 dialysis stations, while a similar dialysis center would typically have 18 stations, the center with 20 stations is likely exerting more effort by investing in extra resources.

The second effort variable is the difference between the *actual* and *predicted* number of full-time equivalent (FTE) staff. Staffing levels are crucial for both reducing patient wait times and ensuring prompt responses to patient needs during treatment (Eliason, 2019). For instance, a patient experiencing low blood pressure during treatment will be attended to quicker if additional staff are available. Staff levels are also related to infection control, as more personnel can focus on cleaning and preparing stations between treatments (Patel et al., 2013). Since dialysis centers hire both full-time and part-time staff, I use full-time equivalents (FTEs), which I define as the sum of the full-time staff and half of the part-time staff.

The last effort variable is the difference between *actual* and *predicted* the number of high-certification FTE staff members. High-certification staff, such as registered nurses, advanced care technicians, and dietitians, require more extensive and costly training compared to lower-certified staff, and are therefore more costly both in hourly wage and annual training. High-certified staff are able to respond more efficiently to complex dialysis complications. Consequently, employing more high-certification staff reflects a willingness to invest in improving patient care.

To create the proxy variables, I estimate the expected number of dialysis stations, FTE staff, and high-certification staff using patient volume, profit status, urbanicity, the age of the dialysis center, and time fixed-effects. These variables allow the predicted values to adjust to patient flows or dialysis center priorities over time. I take the difference between actual and predicted values, and set a binary indicator equal to 1 if the difference is positive, indicating high effort, and 0 otherwise.

For each $k \in \{\text{stations, FTE staff, high certification staff}\}$, the effort estimation takes the form

$$\begin{aligned} S_{jt}^k &= \beta^k n_{jt}^k + \theta^k C_{jt} + \tau_t^k + \varepsilon_{jt}^k \\ \Delta_{jt}^k &= S_{jt}^k - \widehat{S}_{jt}^k \\ E_{jt}^k &= \mathbb{1}\{\Delta_{jt}^k \geq 0\} \end{aligned} \tag{1.3}$$

where $n_{jt}^k$ is the total number of dialysis stations, FTE staff, or high-certification staff at dialysis center $j$ at time $t$, $C_{jt}$ is a vector of facility level characteristics, and $\tau$ are time fixed effects.

The estimated values and correlation with switching are shown in Table 1.4. Less than half of all dialysis centers exert high effort as measured by dialysis stations, full-time staff, and high

certification staff. The average value for dialysis station effort is 0.435, suggesting that around 43% of the sample have more dialysis stations than predicted and are exerting high effort. Around 41% of centers hire more full-time staff than expected, and 39.5% hire more high certification staff than expected. These values are consistent with effort being costly: dialysis stations require a large up-front cost, but can be amortized over the course of several years, whereas staff levels require recurring annual expenditures. The correlation with switching is shown in the bottom three rows. All proxy variables are negatively correlated with patient switching, suggesting that patients are less likely to switch when their center exerts positive effort.

Table 1.4 Summary Statistics for Effort Proxy Variables

| | **Mean** | **S.D.** |
|---|---|---|
| **Effort Proxy** | | |
| Dialysis Stations | 0.435 | (0.496) |
| Full-time Staff | 0.413 | (0.492) |
| High Certification Staff | 0.395 | (0.489) |
| **Correlation with Switching** | | |
| Dialysis Stations | -0.0048 | |
| Full-time Staff | -0.0487 | |
| High Certification Staff | -0.0434 | |

Notes: This table presents the effort proxy variables and the correlation with switching. The effort proxy variables are for the number of dialysis stations, full-time staff members, and high-certification staff members. The unit of observation is a patient-year. Proxy variables are binary. The second panel shows the correlation between the three effort proxy variables a patient's likelihood of switching.

These three variables capture different streams of effort, but it is important to acknowledge their limitations. Effort can manifest in ways not captured by these proxy variables. For instance, a dialysis center may increase efficiency by training current staff, rather than hiring new staff. Patel et al. (2013) show that staff members trained on proper hand hygiene and skin antisepsis can significantly reduce the rate of blood stream related infections, but such improvements are not easily observable in the data.

Additionally, some dialysis centers may allocate resources more effectively through better management practices, such as regular preventative maintenance on dialysis stations or optimizing staff schedules and reducing staff turnover. Profit status and ownership structure can have some effect on this allocation (Grieco and Mcdevitt, 2017), but the full extent is unknown. Further, other managerial decisions like the layout of the dialysis treatment floor or capital decisions such as retiring older dialysis stations are harder to quantify. While the three derived proxy variables provide useful insight into a center's effort, they do not provide a complete picture of all decisions that affect quality.

### 1.4.3 Patient Selection and Measuring Quality

The other threat to identification is the nonrandom assignment of patients to their dialysis center. This selection can affect the likelihood of switching in three ways. First, a dialysis patient's initial choice of treatment center may be based primarily on travel distance. Other studies have shown travel distance to be a large determining factor in initial choice of dialysis centers (Grieco and Mcdevitt, 2017; Eliason et al., 2020) and nursing homes (Zhao, 2016; Hackmann, 2019). I account for this selection by controlling for the log-distance a patient travels to their dialysis center.

Second, a dialysis patient may sort to a center based on unobservable characteristics, such as proximity to their nephrologist or employer. If this is the case, then the decision to switch or not switch could be unrelated to dialysis center quality or published quality scores. I account for this selection by including a rich vector of patient demographics to control for individual preferences. Last, dialysis center quality is influenced by the patients that they treat. For example, a dialysis center located next to a hospital that treats advanced cases of ESRD may attract these patients because of proximity. This dialysis center is then treating a cohort of patients that are sicker than the average dialysis patient. Rather than reflecting actual treatment quality, quality scores will be lower because the patient cohort at this center is less healthy and experience more adverse outcomes, on average, than other dialysis patients. I overcome this effect of patient sorting by estimating risk-adjusted ratios for each dialysis center in each year. Risk-adjusting controls for patient-level differences makes quality comparisons between centers and within a center over time

more meaningful.

I calculate risked adjusted ratios for two key outcomes. The first is the probability that a patient achieves a urea-reduction ratio above 65% for all dialysis sessions in a given year. I refer to this as dialysis adequacy. While this may seem restrictive, Table 1.2b shows that patients have sufficient dialysis adequacy in over 94% of their treatments. The second outcome is the probability that a patient is admitted to a hospital for a dialysis-related infection. Patients have an infection rate of 12.5% each year. These measures represent reliable[17] alternative measures of dialysis center quality (Eliason, 2022). The risk-adjusted ratios transform these measures into relative measures of quality, rather than absolute measures. A risk-adjusted ratio indicates how much better (or worse) a dialysis center performed relative to how they were expected to perform, given their patient roster.

To estimate risk adjusted ratios, I use a logistic regression to estimate the probability that a patient with a given set of characteristics and comorbidities experiences the event. I exclude the year a patient switches dialysis centers to avoid misattributing the event to the incorrect dialysis center; the years in which a patient does not switch are included. The predicted probabilities for each patient at a dialysis center in a year are averaged, giving the risk-adjusted probability. The risk-adjusted ratio is then the ratio of the average observed probability to the risk-adjusted probability:

$$Risk\ Ratio_{jt} = \frac{Observed\ Probability_{jt}}{Predicted\ Probability_{jt}} \tag{1.4}$$

This risk ratio is calculated for each dialysis center-year. Outliers are adjusted by capping values that are above the $99^{th}$ percentile to the $99^{th}$ percentile.

Summary statistics for these quality measures are presented in Table 1.5. The first panel shows the unadjusted and adjusted probabilities that a patient has a urea reduction ratio (dialysis adequacy) greater than 65% for all treatments in a year. The adjusted and unadjusted measures have similar values. The average risk adjusted ratio is 1.012, indicating that patients at dialysis

[17]Using the risk adjusted ratio for mortality gives results inconsistent with other estimates, namely that patients are less likely to switch away from a high-mortality dialysis center. Expected mortality is very sensitive to the risk adjusting variables and is heavily influenced by factors unrelated to the dialysis center, such as medication compliance and lifestyle choices. I therefore omit risk-adjusted mortality in my specification.

centers have, on average, a 1.2% higher likelihood of having a urea reduction ratio above 65% for all dialysis sessions than expected. The second panel shows the unadjusted and adjusted infection rates, which vary by about 1.5 percentage points. The risk ratio is 0.990, indicating that patients at dialysis centers have, on average, a 1% lower likelihood of having an infection than predicted.

Table 1.5 Predicted Quality Risk Ratios

| | **Mean** | **S.D.** |
|---|---|---|
| **Dialysis Adequacy** | | |
| Unadjusted Pr(Dialysis Adequacy $>$ 65%) | 79.345 | (16.084) |
| Adjusted Pr(Dialysis Adequacy $>$ 65%) | 79.499 | (8.018) |
| Dialysis Adequacy Risk Ratio | 1.012 | (0.186) |
| **Infection Rates** | | |
| Unadjusted Infection Rate | 12.505 | (8.780) |
| Adjusted Infection Rate | 10.951 | (1.066) |
| Infection Rate Risk Ratio | 0.990 | (0.5534) |
| **Center-Years** | 79,324 | |

Notes: This table presents summary statistics for the risk-adjusted ratios for dialysis adequacy and infection rates. Risk ratios are first estimated using individual patient characteristics and predicting the dialysis adequacy likelihood and infection rate. Risk-adjusters include the patient's 5-year age bracket interacted with binary indicators for male and race including white, Hispanic, black and Asian; comorbidities including alcohol use, atherosclerotic heart disease, cancer, congestive heart failure, chronic obstructive pulmonary disease (COPD), stroke, diabetes, drug use, high blood pressure, whether a patient is ambulatory or needs assistance, peripheral vascular disease, and tobacco use; number years on dialysis treatment interacted with the age a patient started dialysis; the primary cause of kidney failure; the quintile of glomerular filtration rate, which is a measure of how efficient the kidneys are at removing toxins; the quintile of BMI; the year a patient started dialysis; and year fixed-effects. I exclude the year in which a patient switches to avoid misattributing the outcome with the incorrect treatment center.

## 1.5 Empirical Specification and Results

### 1.5.1 Published Quality and Switching

To estimate how published quality scores influence patient preference, I first test whether patients are generally sensitive to dialysis center quality. Dialysis patients actively choose their dialysis provider in each period, and while many remain at their current provider, some choose to switch. As shown in Figure 1.3 and Table 1.2b, the annual unconditional rate of switching is 6.45%. Eliason et al. (2020) cites that 1.3% of patient-months represent a permanent switch away from a facility, and Bertuzzi et al. (2023) captures a 0.8% rate of switching in a given month. If patients are sensitive to quality, and if published quality scores accurately reflect quality, then patients at dialysis centers with lower published scores will switch more frequently than patients at dialysis centers with higher quality scores.

To formalize this, let $Switch^*$ be a latent measure of an individual's desire to switch providers. A patient will switch to a different dialysis center when $Switch^* > 0$. Define $Switch^*$ as

$$Switch^*_{ijt} = \beta_0 + \beta_{jt}\mathbf{Q}_{jt} + \gamma_{it}\mathbf{C}_{jt} + \theta_{it}\mathbf{X}_{it} + \varepsilon_{ijt} \tag{1.5}$$

where $Q_{jt}$ is a vector of dialysis center quality, $C_{jt}$ are dialysis center characteristics, and $X_{it}$ are patient characteristics. The probability that we observe a patient switching is equal to the probability that $Switch^*$ is positive:

$$P(Switch_{ijt} = 1|\mathbf{Q, C, X}) = P(Switch^*_{ijt} > 0|\mathbf{Q, C, X}) \tag{1.6}$$

Combining these two equations, the likelihood of a patient switching can be expressed as a condi-

tional probability and simplified to:[18]

$$P(Switch_{ijt} = 1|\mathbf{Q, C, X}) = \beta_0 + \beta_{jt}\mathbf{Q}_{jt} + \gamma_{it}\mathbf{C}_{jt} + \theta_{it}\mathbf{X}_{it} \tag{1.7}$$

where $\mathbf{Q}_{jt}$ contains the published quality scores and the two risk-adjusted ratios; $\mathbf{C}_{jt}$ contains the three effort proxy variables and dialysis center characteristics from Table 1.3; and $\mathbf{X}_{it}$ contains dialysis patient characteristics from Tables 1.2a and 1.2b. By assuming $\varepsilon_{ijt}$ has a uniform distribution, we then obtain a linear probability model. The benefit of the LPM in this setting is the ease of interpretation, which is the change in the likelihood of changing dialysis centers from a one-point increase in the quality score. I show in the Appendix A.3 that the results are robust to estimating a logit model. The coefficients $\beta_{jt}$, $\gamma_{jt}$, and $\theta_{it}$ capture the effects of quality, center characteristics, and patient characteristics, respectively, on the probability of switching. If patients respond to lower quality by increasing their likelihood of switching, then coefficient on published quality scores will be negative.

In my estimations, I use a bootstrapping procedure to estimate appropriate standard errors, which accounts for the measurement error when estimating the risk-ratios. I perform the following two-step bootstrapping procedure. In the first step, I randomly sample dialysis centers (with replacement) from the original data set. I estimate the risk-adjusted ratios using the logistic regression. In the second step, I use the risk-adjusted ratios in the primary estimation. I repeat this bootstrapping procedure 250 times, and report the bootstrapped standard errors.

The results from this estimation are presented in Table 1.6 using data from 2012 through 2019. I progressively add more control variables and observe how the effect of published quality scores

[18]This is derived using the following:

$$\begin{aligned}
P(Switch_{ijt} = 1|\ \mathbf{Q, C, X}) =& P(Switch^*_{ijt} > 0|\ \mathbf{Q, C, X}) \\
=& P(b_0 + b_{jt}\mathbf{Q}_{jt} + g_{jt}\mathbf{C}_{jt} + h_{it}\mathbf{X}_{it} + \varepsilon_{ijt} > 0|\ \mathbf{Q, C, X}) \\
=& P(\varepsilon_{ijt} > -b_0 - b_{jt}\mathbf{Q} - g_{jt}\mathbf{C}_{jt} - h_{it}\mathbf{X}|\mathbf{Q, C, X}) \\
=& 1 - P(\varepsilon_{ijt} \leq b_0 + b_{jt}\mathbf{Q} + g_{it}\mathbf{C}_{jt} + h_{it}\mathbf{X}|\mathbf{Q, C, X}) \\
=& 1 - F_{\varepsilon|\mathbf{Q, C, X}}(b_0 + b_{jt}\mathbf{Q} + g_{jt}\mathbf{C}_{it} + h_{it}\mathbf{X}|\mathbf{Q, C, X})
\end{aligned}$$

where $F_{\varepsilon_{ijt}|\mathbf{Q, C, X}}$ is the distribution of $\varepsilon_{ijt}$. Changing the assumptions around the distribution of $\varepsilon$ informs the method of estimation. The error term, $\varepsilon$, is assumed to be uniformly distributed and we obtain a linear probability model. Otherwise, we obtain a probit model if we assume a normal distribution, and a logit model if we assume a logistic distribution.

on switching changes. Column 1 only includes the published quality score and time fixed effects. Column 2 adds dialysis center effort proxies and travel distance, and column 3 adds patient and dialysis center characteristics. I explore if the effect on switching is dependent on patient health characteristics or other measures of provider quality, which are separately included in columns 4 and 5, respectively. Column 6 is my preferred specification and includes all control variables. Coefficients represent a percentage point change in the probability of switching.

Table 1.6 Published Quality Scores and Switching Probabilities
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health | (5) Facility Quality | (6) All |
|---|---|---|---|---|---|---|
| **Quality** | | | | | | |
| QIP Score | -0.0313*** | -0.0318*** | -0.0284*** | -0.0259*** | -0.0201*** | -0.0197*** |
| | (0.0038) | (0.0036) | (0.0035) | (0.0034) | (0.0033) | (0.0033) |
| Risk Adjusted Adequate Ratio (10%) | | | | | -0.2619*** | -0.1916*** |
| | | | | | (0.0364) | (0.0370) |
| Risk Adjusted Infection Ratio | | | | | 0.0532*** | 0.0467*** |
| | | | | | (0.0109) | (0.0112) |
| **Effort Proxy** | | | | | | |
| Effort: Stations | | -0.4024*** | -0.2576** | -0.2567** | -0.2514** | -0.2523** |
| | | (0.0740) | (0.1123) | (0.1127) | (0.1115) | (0.1119) |
| Effort: High Skill Staff | | -0.5809*** | -0.2739*** | -0.2708*** | -0.2586*** | -0.2593*** |
| | | (0.0743) | (0.0885) | (0.0885) | (0.0877) | (0.0878) |
| Effort: FTE Staff | | -0.3858*** | -0.3890*** | -0.3170*** | -0.3623*** | -0.3585*** |
| | | (0.0776) | (0.0929) | (0.0931) | (0.0921) | (0.0924) |
| **Patient Health Characteristics** | | | | | | |
| Dialysis Adequacy | | | | -0.3173*** | | -0.2825*** |
| | | | | (0.0176) | | (0.0183) |
| Infection Rate | | | | 0.4594*** | | 0.4101*** |
| | | | | (0.0380) | | (0.0424) |
| Log(Distance) (10%) | | 0.1155*** | 0.1064*** | 0.1055*** | 0.1059*** | 0.1052*** |
| | | (0.0039) | (0.0038) | (0.0038) | (0.0378) | (0.0038) |
| Mean Dep. Var | 6.374% | 6.374% | 6.374% | 6.374% | 6.374% | 6.374% |
| Year FE: | Y | Y | Y | Y | Y | Y |
| Effort: | N | Y | Y | Y | Y | Y |
| Patient Characteristics: | N | N | Y | Y | Y | Y |
| Patient Health: | N | N | N | Y | N | Y |
| Facility Quality: | N | N | N | N | Y | Y |
| Observations | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: Estimation of the effect of published quality scores on the probability of switching. Unless otherwise indicated, coefficients are multiplied by 100 and represent the percentage point change in the probability of switching. Column 1 only uses published scores; column 2 adds dialysis center effort and the log of distance; column 3 adds patient and dialysis center characteristics; column 4 includes patients health characteristics but no center quality measures; column 5 includes dialysis center quality measures but no patient health characteristics; column 6 includes both patient health characteristics and dialysis center quality measures. Coefficients and standard errors are estimated using 250 repetitions of a two-step bootstrap procedure. In the first step, dialysis centers are randomly sampled (with replacement) from the original dataset, and both risk ratios are re-estimated within each sampled cluster. In the second step, the risk ratios are used in Equation 1.7 to estimate the coefficients of interest. Bootstrapped standard errors are comparable to standard errors clustered at the dialysis center level. Select coefficients are excluded for brevity.

These results show that published quality scores and the likelihood of switching have a negative relationship. From column 6, patients at a dialysis center with a one point higher published quality score are 0.019 percentage points less likely to switch.[19] The adjusted risk ratios and effort proxy variables have signs and magnitudes that agree with the measure. For example, column 6 shows that patients at a dialysis center with a 10% higher probability of having an adequate urea reduction ratio for the entire year are 0.1916 percentage points less likely to switch, while patients at a dialysis center with an infection ratio 10% higher are 0.046 percentage points more likely to switch. The effort proxy variables also affect switching: column 6 shows that patients at dialysis centers exerting more effort through stations, high-certification staff, and more FTE staff are 0.2523, 0.2593, and 0.3585 percentage points less likely to switch, respectively, than patients at centers not exerting high effort. The effect of other dialysis center quality measures is more pronounced than patient health attributes. The difference in the coefficient on published quality from column 3 to column 4 when adding patient health is only 0.003 base points, but 0.009 base points going from column 3 to column 5 when adding other quality measures.

The estimates for patient health characteristics are consistent with Bertuzzi et al. (2023), where an adverse health event affects the probability of changing dialysis centers. Column 6 shows that a patient hospitalized with an infection has an increased probability of switching of approximately 0.410 percentage points. Travel distance is included in the table because the distance between a patient and their treatment center is one of the most important factors when choosing a center, which has been well documented (Eliason, 2022; Grieco and Mcdevitt, 2017). This is the case in my setting: increasing travel distance by 10% increases the probability of switching by approximately 0.1 percentage points, which is consistent across all estimations. In Appendix A.3, I show that this estimation is robust to other specifications, such as a non-linear logistic estimation, as well as accounting for unobserved heterogeneity with patient, dialysis center, and market fixed-effects. Additionally, I show in Appendix A.4 that the current quality scores have the largest impact on switching when compared to prior quality scores, suggesting that patients are not using the trend

[19] These estimates include patients that switch more than once. Excluding patients that switch more than once does not substantively alter effect. Additionally, quality scores have a similar effect at higher levels of switching.

of quality when making their decision.

While the effect of quality scores on changing dialysis centers seems mathematically small, the economic significance is considerable. Table 1.7 shows the elasticity of a 10% change in the published quality score, and the probability of switching for patients at the $10^{th}$ and $90^{th}$ percentiles. Each column is estimated from the corresponding column in Table 1.6. Moving from column 1 to column 6, an average patient at a dialysis center with a 10% higher published quality score is between 3.01% and 2.08% less likely to switch, respectively. When considering the estimates from column 6, patients at a center with a score in the $10^{th}$ percentile switch at a rate of 6.41%, but patients at a center with a score in the $90^{th}$ percentile switch at a rate of 5.31%, which is roughly a 19% (1.1 percentage point) decrease. Assuming the flow of patients into a dialysis center is zero and the dialysis center is treating 68 patients, the estimates from column 1 suggest that the dialysis center will lose 5 patients if they are in the 10th percentile, but a center in the 90th percentile will only lose 3.75 patients. In column 6, these estimates drop to 4.36 and 3.61, respectively, and represent a difference in expected revenue of roughly $30,000. Overall, the results in Tables 1.6 and 1.7 show a robust negative relationship between published quality scores and switching probabilities.

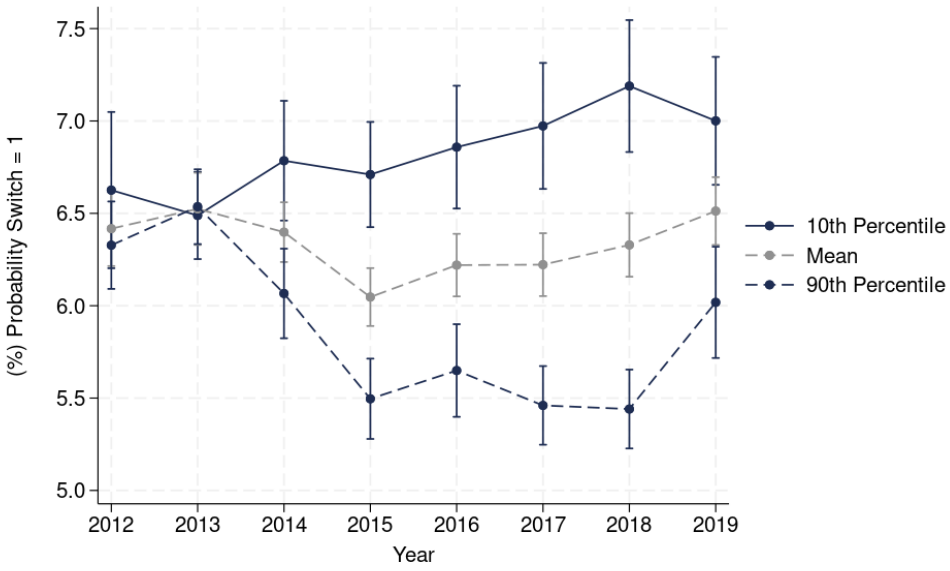
Table 1.7 Elasticity and Marginal Effects of Published Quality
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health | (5) Facility Quality | (6) All |
|---|---|---|---|---|---|---|
| QIP Elasticity | -3.0144 | -3.3329 | -2.9990 | -2.7302 | -2.1261 | -2.0847 |
| *(10%/% change)* | (0.4041) | (0.3977) | (0.3759) | (0.3682) | (0.3579) | (0.3562) |
| 10th Percentile | 7.3566 | 6.8543 | 6.7044 | 6.6300 | 6.4262 | 6.4191 |
| 90th Percentile | 5.5437 | 5.0206 | 5.0632 | 5.1350 | 5.2956 | 5.3099 |
| Difference (pp) | 1.8129 | 1.8337 | 1.6412 | 1.4950 | 1.1306 | 1.1092 |
| Difference (%) | 28.11 | 30.88 | 27.89 | 25.41 | 19.29 | 18.91 |
| Year FE: | Y | Y | Y | Y | Y | Y |
| Effort: | N | Y | Y | Y | Y | Y |
| Patient Characteristics: | N | N | Y | Y | Y | Y |
| Patient Health: | N | N | N | Y | N | Y |
| Facility Quality: | N | N | N | N | Y | Y |

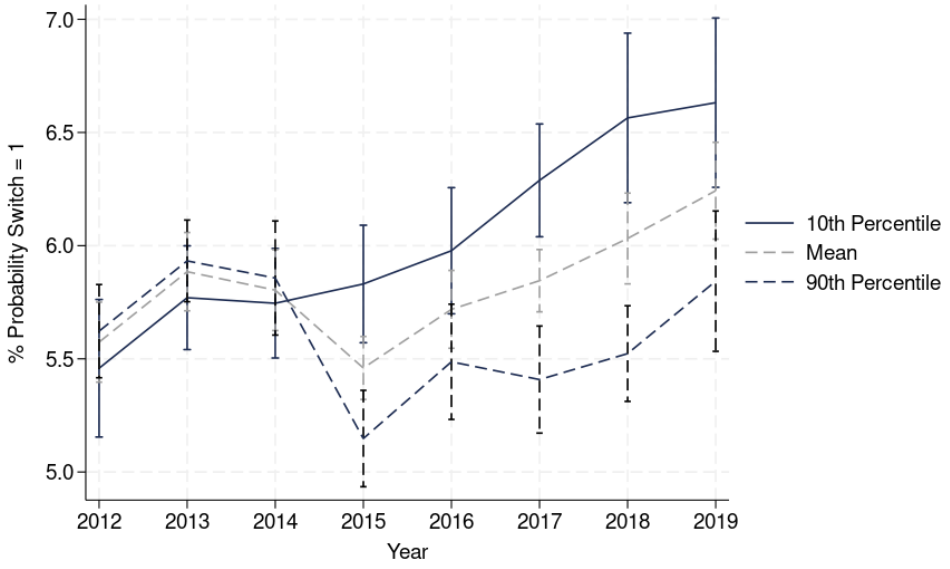
Notes: This table shows the elasticity and marginal effects of published quality scores, using data from 2012-2019. Each column corresponds to the same column in Table 1.6. All estimations include other quality measures, effort proxy variables, provider characteristics and patient attributes, and year fixed-effects. Standard errors are derived using the two-step bootstrapping procedure. Elasticity is scaled to show the % change due to a 10% increase in the quality score.

Figure 1.5 shows the progression of the predicted likelihood of switching for patients at dialysis centers in the $10^{th}$ and $90^{th}$ percentiles of quality scores for each year; patients at a center with an average score are also shown. The top panel shows the results from estimating the first column of Table 1.6, and the bottom panel shows the results from estimating the last column. Standard errors are derived from the two-step bootstrap procedure.[20] The rate of switching is similar from 2012-2014, but diverges afterwards. The difference between the $10^{th}$ percentile and the average score is consistent from year to year, while the magnitude between the average and $90^{th}$ percentile increases slightly each year.

[20]Performing the estimation with standard errors clustered at the dialysis center level produces a nearly identical figure.




(a) No Controls, Specification 1




(b) All Controls, Specification 6

Figure 1.5 Predicted Probability of Switching Dialysis Centers

Notes: Probability of switching for patients at dialysis centers in the $10^{th}$, mean, and $90^{th}$ percentiles of quality scores for each year. Dialysis centers with quality scores in the $10^{th}$ percentile are the lowest quality dialysis centers. The top panel shows the results from estimating the first column of Table 1.6, and the bottom panel shows the results from the estimation of the last column. Standard errors are derived using the two-step bootstrapped procedure.

### 1.5.2 Inferring Dialysis Center Quality

I now consider the salience of published quality scores. If the Quality Incentive Program is effective at influencing patient behavior, then the introduction of these scores will affect the likelihood of a patient switching to a different dialysis center. A key challenge is classifying dialysis centers as high or low quality prior to the publication of scores. Ideally, quality scores could be calculated prior to 2012 using the same methodology as CMS, and we would be able to observe how patients differentially switch once scores are published. Kepler et al. (2024) uses the same measures from 2012 to estimate scores in 2009-2011. However, the data used for scores in the years prior to 2012 has limited availability and little variation, making estimated scores uninformative in my setting. Instead, I use quality after 2012 to infer quality before 2012 using three methods: average observed quality scores; the trend of quality sores relative to the sample average; and predicted quality.

A key assumption is that, without published scores, patients at both high and low quality centers would exhibit similar switching trends. Switching rates may still differ based on patients' prior beliefs about quality. Although this assumption is not directly testable, several factors suggest its validity. First, information is disseminated to all dialysis centers at the same time and changes to quality inputs and other requirements are imposed on all dialysis centers with little exception,[21] removing any first-mover advantage. Facilities may respond differently to the Quality Incentive Program depending on their resources and profit status (Grieco and Mcdevitt, 2017), however, controlling for profit status and other dialysis center characteristics should alleviate this concern. Finally, as I show in the next section, interacting inferred quality with binary year variables reveals a common trend prior to 2012 and a divergence afterwards.

Another important assumption is that dialysis centers revealed to be high or low quality would be similarly categorized prior to scores being released; that is, a low quality dialysis center today was a low quality dialysis center yesterday. This rules out any sudden jumps in quality, as well as a center being low quality and then reclassified as high quality. Though some centers may change

[21] One exception is due to size: dialysis centers with less than 11 patients are typically not included as a way to protect patient confidentiality

quality over time, controlling for dialysis adequacy and infection risk ratios accounts for these variations. I informally show that this assumption is not too restrictive in Appendix A.5.

To formalize patient switching, I estimate the following model:

$$P(Switch_{ijt} = 1|\mathbf{Q, C, X}) = \beta_0 + \beta_{jt}\mathbf{Q}_{jt} + \delta_0 \textit{Post} + \delta_{jt}\mathbf{Q}_{jt}Post + \gamma_{jt}\mathbf{C}_{jt} + \theta_{it}\mathbf{X}_{it} \tag{1.8}$$

which is analogous to Equation 1.7, but instead includes an indicator variable set to 1 for the time periods after 2012 interacted with the quality measures of interest. In a separate specification, *Post* is set to 1 starting in 2014 when quality scores have meaningful variation. The other quality measures are not interacted with the *Post* indicator, but are instead included in $C_{jt}$. In separate estimations, I use three methods of classifying quality as $Q_{jt}$: average quality scores; the trend of quality scores; and predicted quality scores. The interaction with $Post$ shows the change in the likelihood of switching before and after 2012 or 2014, depending on the specification. The derivation of this equation is identical to Equation 1.7.

### 1.5.3 Average Quality Scores

My first group of estimates exploits a dialysis center's average published quality score after 2012 to infer quality prior to 2012. For each dialysis center, I find the average quality for 2012-2019, 2014-2019, 2016-2019, and 2018-2019. I then assign this static average quality score to earlier years. Classifying dialysis centers using four separate windows of quality scores tests whether the effects on switching are robust to different definitions of average quality and the increasing number of score inputs shown in Table 1.1.

My main specification includes adjusted risk ratios, effort proxies, dialysis center and patient characteristics, and time fixed effects, following the estimation in Column 6 of Table 1.6. Table 1.8 shows the results for different windows of average quality scores. Column 1 uses the quality scores from 2012-2019; column 2 uses the scores from 2014-2019; column 3 uses the scores from 2016-2019; and column 4 uses the scores from 2018-2019. The top row reports the key coefficient: the interaction of average quality with the post-2012 period. In column 1, the coefficient of -0.054 indicates that a one-point increase in a dialysis center's future average quality score reduces a

patient's probability of switching by 0.054 percentage points once scores are published. Column 2 reduces this effect by half, primarily because 2012 and 2013 have scores out of 30, and 2014 is the first year with scores out of 100. Column 3 has a similar point estimate to column 2. Last, column 4 indicates that patients at a dialysis center with an average score in 2018 and 2019 that is one point higher is 0.018 percentage points less likely to switch once scores are published. These four estimations provide evidence that patients are responsive to learning about the quality of their dialysis center.

Table 1.8 Four Windows of Average Quality with 2012 Exposure Year
Data from 2006-2019

| Pr(Switch = 1) | (1) Mean 2012-2019 | (2) Mean 2014-2019 | (3) Mean 2016-2019 | (4) Mean 2018-2019 |
|---|---|---|---|---|
| **Quality** | | | | |
| (Average QIP)*Post | -0.0543*** | -0.0298*** | -0.0264*** | -0.0182*** |
| | (0.0085) | (0.0065) | (0.0063) | (0.0054) |
| Post | 4.1687*** | 2.9206*** | 2.5765*** | 1.9762*** |
| | (0.5496) | (0.5097) | (0.4714) | (0.3814) |
| Average QIP | -0.0119 | 0.0033 | -0.0080 | -0.0074 |
| | (0.0094) | (0.0069) | (0.0055) | (0.0055) |
| Year FE: | Y | Y | Y | Y |
| Effort: | Y | Y | Y | Y |
| Patient Characteristics: | Y | Y | Y | Y |
| Patient Health: | Y | Y | Y | Y |
| Facility Quality: | Y | Y | Y | Y |
| Observations | 3,020,479 | 3,020,479 | 3,020,263 | 3,019,527 |

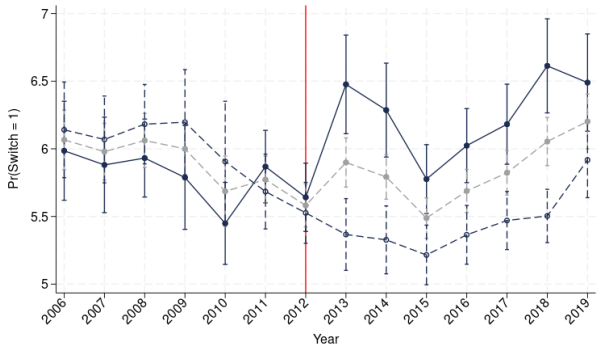
Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: Estimation of the probability of switching based on average published quality scores for 2012-2019, 2014-2019, 2016-2019, and 2018-2019. Average score is applied to the years prior to window used. The year of exposure is 2012 when quality scores are first made available. Data used in estimation is from 2006-2019. All columns include year fixed effects, effort proxy variables, patient characteristics and health, and dialysis center risk ratios. Coefficients and standard errors are estimated using 250 repetitions of the two-step bootstrap procedure.

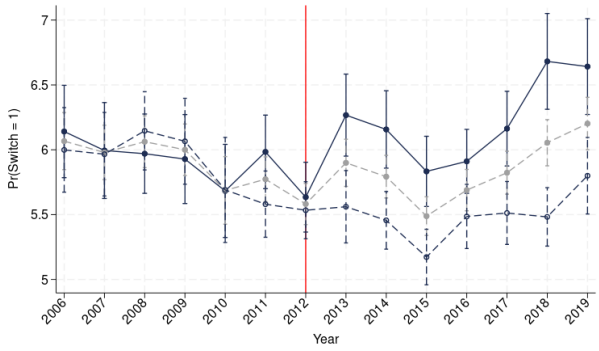
These effects are further illustrated in Figure 1.6. I show the predicted likelihood of switching in each year by replacing *Post* with year indicators. This dynamic specification allows me to

informally test for pre-trends, i.e. whether the likelihood of switching is changing prior to score disclosure. Additionally, I can observe whether patients are differentially switching depending on the quality score. I estimate the switching likelihood for dialysis centers with a score in the $10^{th}$ percentile, at the sample average, and in the $90^{th}$ percentile. The red line indicates the year 2012, when score are officially published. Panel 1.6a shows the estimation using average quality from 2012-2019; panels 1.6b, 1.6c, and 1.6d show the estimations using the time periods 2014-2019, 2016-2019, and 2018-2019, respectively. All four figures show a divergence after 2012, with patients at lower quality dialysis centers more likely to switch than those at higher quality dialysis centers.

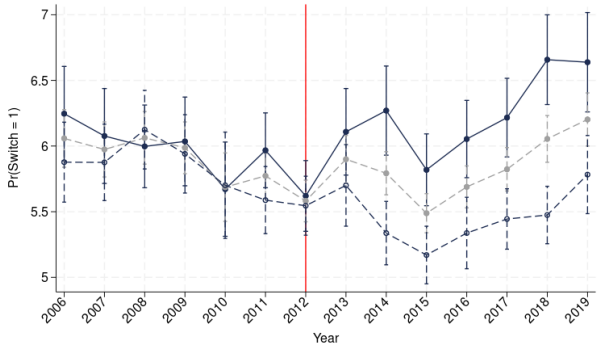
Panel 1.6d reveals that the switching probabilities in 2012 and 2013 remain similar to the pre-2012 period, with divergence starting in 2014. This suggests that 2012 and 2013 may be weak indicators of treatment timing. Scores in 2012 and 2013 lack sufficient variation and are close to the maximum, suggesting that patients may either believe they are at a high quality dialysis center and do not switch as a result, or are not able to compare their dialysis center's quality to the national average. Either scenario results in minimal changes in patient behavior. But in 2014, patients begin seeing more variation in scores and potentially more separation from the national average used as a comparison, as shown on the scorecard in Figure 1.1.



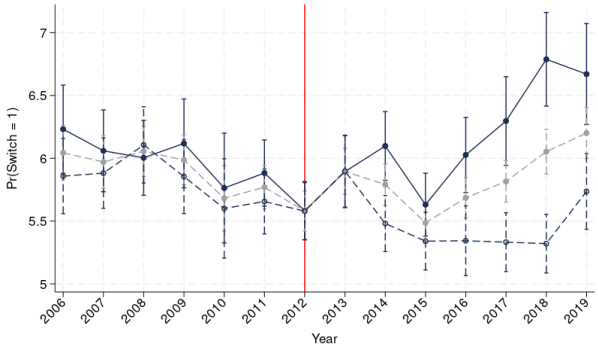

(a) Average quality, 2012 through 2019




(b) Average quality, 2014 through 2019




(c) Average quality, 2016 through 2019




(d) Average quality, 2018 through 2019

Figure 1.6 Probability of Changing Dialysis Centers Using Average Quality Scores
Notes: Estimation of the probability of switching for each year using different windows to calculate average quality. The top solid line are patients at dialysis center's in the $10^th$ percentile of average quality; the gray dotted line are patients at centers with an average score at the sample mean, and the bottom blue dotted line are patients are the $90^th$ percentile of average quality. Quality scores are estimated for the indicated time frame and applied to the years prior to scores being published, 2006-2011. The red line indicates 2012, the first year that quality scores are publicly available. Standard errors are derived using the two-step bootstrapped procedure.

The quality scores in 2012 and 2013 are out of 30 and exhibit little between-center variation. I estimate the same specification from Table 1.8 using 2014 as the first treated year. These results are shown in Table 1.9. The estimates are stable across all four columns, with column 1 using scores from 2012 through 2019, column 2 using 2014 through 2019, column 3 using 2016 through 2019 and column 4 using 2018 through 2019. The estimate from column 1 shows that, after 2014, patients at a dialysis center with an average quality score 1 point higher decrease their probability of switching by 0.037 percentage points when scores are published. Similarly, the estimate in column 4 shows that this probability decreases slightly to 0.028. These estimates suggest that dialysis

patients are responsive to quality scores when they are published, and scores are more effective after 2014 when there is sufficient variation.

Table 1.9 Four Windows of Average Quality with 2014 Exposure Year
Data from 2006-2019

| Pr(Switch = 1) | (1) Mean 2012-2019 | (2) Mean 2014-2019 | (3) Mean 2016-2019 | (4) Mean 2018-2019 |
|---|---|---|---|---|
| **Quality** | | | | |
| (Average QIP)*(Post 2014) | -0.0377*** | -0.0273*** | -0.0312*** | -0.0278*** |
| | (0.0078) | (0.0060) | (0.0060) | (0.0051) |
| Post 2014 | 3.1641*** | 2.7306*** | 2.8981*** | 2.5826*** |
| | (0.5120) | (0.4701) | (0.4430) | (0.3686) |
| Average QIP | -0.0054** | -0.0087*** | -0.0092*** | -0.0051** |
| | (0.0084) | (0.0064) | (0.0058) | (0.0048) |
| Year FE: | Y | Y | Y | Y |
| Effort: | Y | Y | Y | Y |
| Patient Characteristics: | Y | Y | Y | Y |
| Patient Health: | Y | Y | Y | Y |
| Facility Quality: | Y | Y | Y | Y |
| Observations | 3,020,479 | 3,020,479 | 3,020,263 | 3,019,527 |
| Bootstrapped standard errors with 250 replications | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | |

Notes: Estimation of the probability of switching based on average published quality scores, using 2014 as the exposure year. Average quality scores are calculated using published scores from 2012-2019, 2014-2019, 2016-2019, and 2018-2019. The average quality score is applied to all years prior to the window. Data used in the estimation is from 2006-2019. All columns include year fixed effects, effort proxy variables, patient characteristics and health indicators, and dialysis center risk ratios. Standard errors are estimated using 250 repetitions of the two-step bootstrap procedure.

Last, I plot the estimated coefficients of column 4 in Figure 1.7 by replacing *Post* with year dummy variables. The reference year is 2013, the year prior to scores being re-scaled out of 100. Prior to 2013, there is no discernible difference in the likelihood of switching when considering the average quality score. However, after 2013, the likelihood of switching decreases as the average quality score increases and, except for 2015, remains negative.

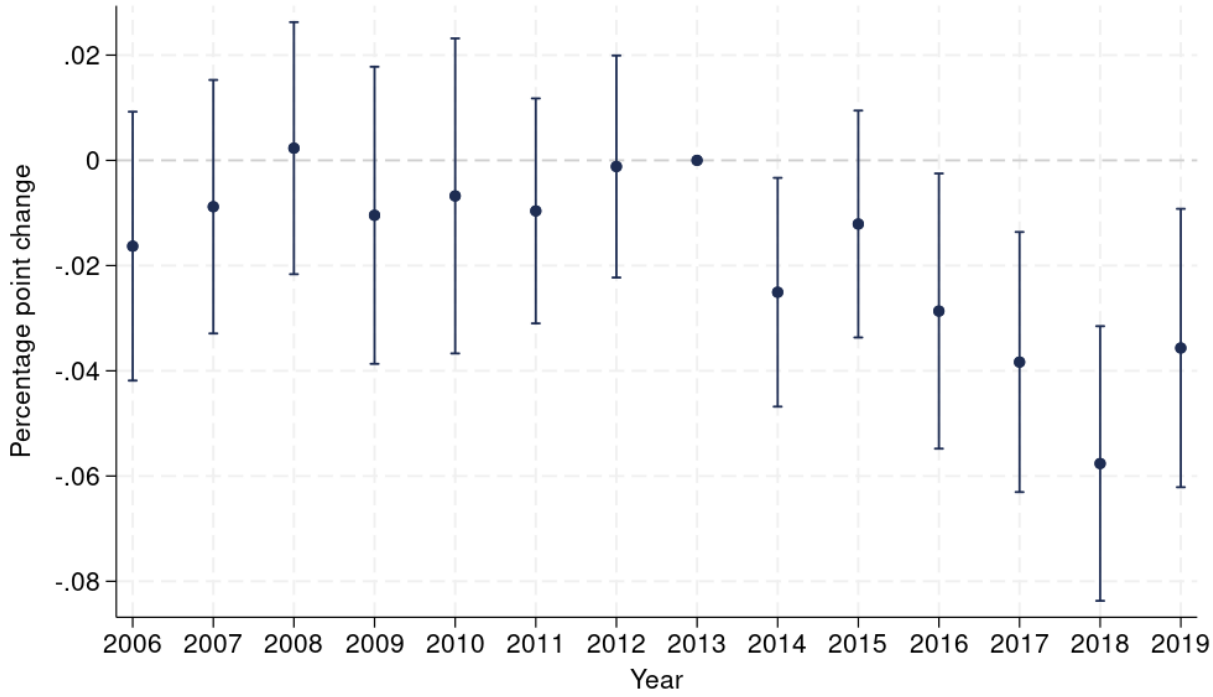



Figure 1.7 Probability of Changing Dialysis Centers

Notes: Coefficient plot using the specification in Column 4 of Table 1.9. Average quality is interacted with year indicator variables. The reference year is 2013. Standard errors are derived using the two-step bootstrapped procedure.

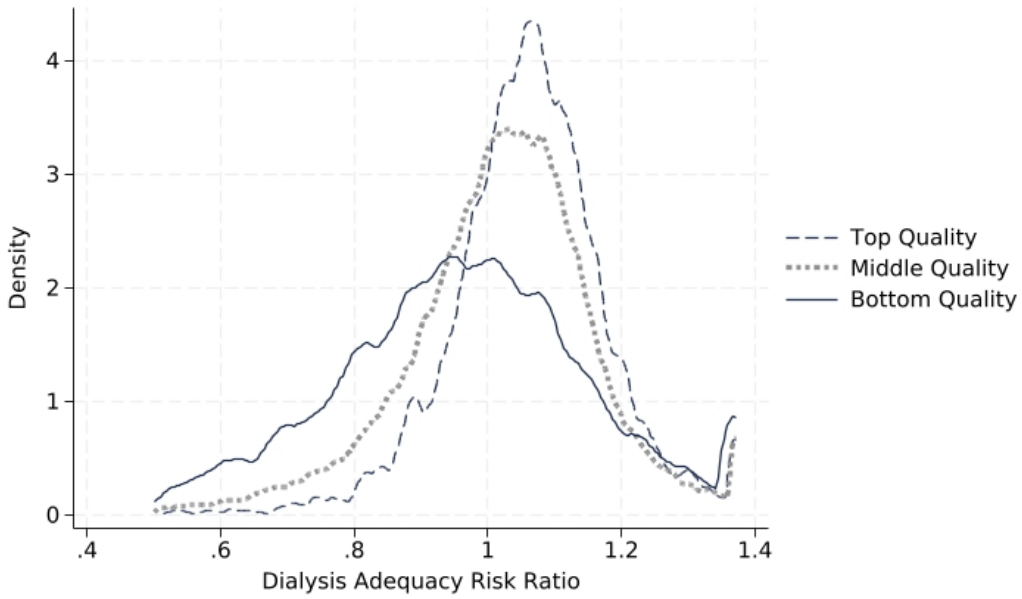
### 1.5.4 Quality Relative to the Sample Average

Next, I use the trend of quality scores to infer pre-2012 quality. I group dialysis centers into bottom, middle, and top quality types by determining how many years their annual quality score is below or above the sample average. Over the 8-year period of published quality scores, dialysis centers with no years above the sample average are classified as bottom quality, while those with all 8 years above the sample average are considered top quality. Dialysis centers that fall between these two extremes form the middle quality group. This classification is retroactively applied to dialysis centers prior to 2012, establishing a consistent quality designation for the entire time frame.

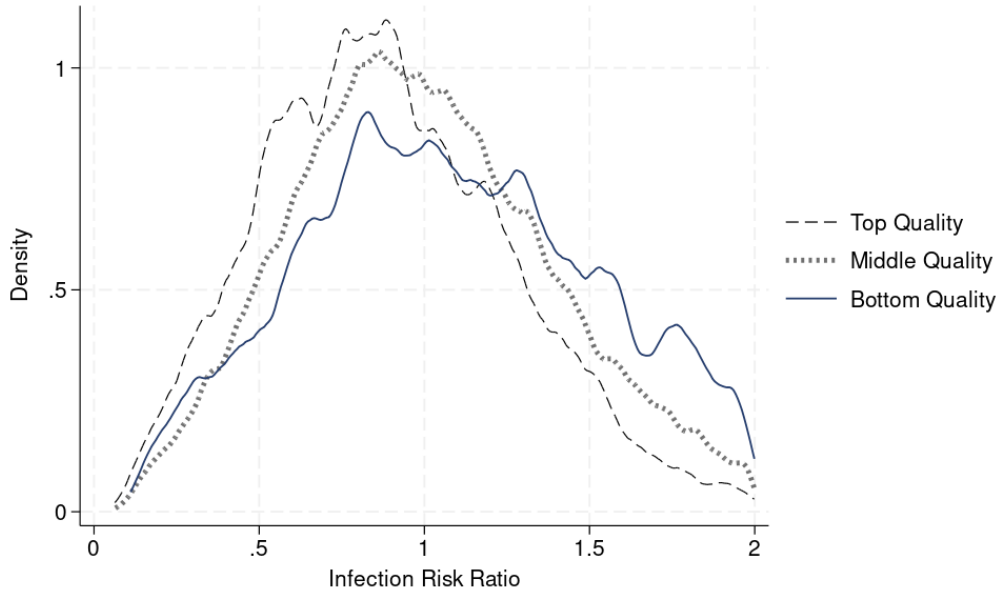
I view patients at bottom type dialysis centers as the treated group. Ramanarayanan and Snyder (2012) suggest that patients may be more responsive to learning negative information about their provider, and information about poor quality may provide a shock to a patient's perception about their dialysis center. In Dranove and Sfekas (2008), hospitals receiving a report card indicating that

quality is lower than what patients expected experience a decrease in market share, but a negligible response is observed for report cards indicating high quality. Dialysis patients have a belief about quality prior to 2012. A dialysis center's published quality score provides a shock to this belief, revealing the quality type of the center. I use the bottom, middle, and top quality designation as an indicator for this shock. This criterion places 7.5% of the sample as top quality and 6.25% as bottom quality dialysis centers, and the remaining 86.25% in the middle-quality category.

The three categories align with the other quality measures. The distributions of both risk ratios for each category are shown in Figures 1.8a and 1.8b. The dialysis adequacy risk ratio is shifted to the right for top quality dialysis centers, indicating that patients at top quality dialysis centers are more likely to have adequate dialysis sessions. The distribution is shifted the left for bottom quality centers. Similarly, the top quality dialysis centers have an infection risk ratio distribution shifted to the left, indicating that they have a lower infection rate than predicted, and vice versa for bottom quality centers.




(a) Dialysis Adequacy Risk Ratio




(b) Infection Risk Ration

Figure 1.8 Risk Ratio Distribution by Quality Group

Notes: The distributions of dialysis adequacy risk ratio and infection rate risk ratio for bottom, middle, and top quality dialysis centers are shown. Panel A shows the distribution of the dialysis adequacy risk ratio. I restrict the distribution to about two standard deviations above, which gives a distribution between 0 and 1.5. The distribution for bottom quality dialysis centers is wider than the distribution for middle and top quality centers. Panel B shows the infection rate risk ratio. The values are restricted between 0 and 2, which about two standard deviations above the mean. Distributions are similar, but bottom quality centers are shifted to the right, consistent with their grouping.

I estimate a slightly modified version of Equation 1.8, interacting a *Post* indicator with the three quality groups. I define $Q_{jt} \in \{$*Bottom, Middle, Top*$\}$. The coefficients on the interaction term of *Q* and *Post* are the outcome of interest: they reveal how patients at different dialysis center quality types respond to learning about their center's quality. Patients in the *Top* category are the reference group. If scores are effective, then the interaction coefficient should be positive, that is, patients learning they are at a low quality dialysis center will increase their likelihood of switching compared to patients learning they are at a high quality dialysis center. In an additional estimation, I use 2014 as the exposure year. Both risk ratios are included in $C_{jt}$ and are not interacted with the *Post* indicator.

I present the results from this estimation in Table 1.10. Column 1 uses 2012-2019 as the *Post* period, and column 2 instead uses 2014-2019 as the *Post* period. Both columns control for dialysis adequacy and infection rate risk ratios, effort proxies, and dialysis center characteristics, in addition to patient health, patient characteristics, and year fixed effects. The first estimate indicates that the likelihood a patient at a bottom-quality dialysis center switches increases by 1.189 percentage points compared to those at top-quality centers. Patients at middle quality dialysis centers are 0.23 percentage points less likely to switch than those at top quality dialysis Centers, but the effect is not statistically significant. In column 2, the estimates decrease only slightly. Patients at bottom quality centers are 1.184 percentage points less likely to switch than patients at top quality dialysis centers. Patients at middle quality centers are 0.207 percentage points more likely to switch than those at top quality centers, but this effect is not statistically significant. Both of these columns show that patients in the bottom quality group are responsive to disclosing the quality of their dialysis center.

Table 1.10 Grouped Quality Using Years Above Sample Average
Years 2006-2019

| Pr(Switch=1) | (1)<br>2012-2019 | (2)<br>2014-2019 |
|---|---|---|
| **Quality** | | |
| (Bottom)*(Post) | 1.1891** | |
| | (0.5622) | |
| (Middle)*(Post) | 0.2033 | |
| | (0.1904) | |
| (Bottom)*(Post 2014) | | 1.1844** |
| | | (0.4770) |
| (Middle)*(Post 2014) | | 0.2073 |
| | | (0.1649) |
| Bottom | -0.0124 | 0.0990 |
| | (0.1784) | (0.4677) |
| Middle | 0.2766 | 0.3068** |
| | (0.1784) | (0.1517) |
| Post | 0.5627** | |
| | (0.2387) | |
| (Post 2014) | | 0.5527** |
| | | (0.2220) |
| Bootstrapped standard errors with 250 replications | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | |

Notes: This table shows estimations of the probability of switching based on bottom, middle, and top groups of quality. Grouping is determined using the number of years a dialysis center's quality score is above the sample average. Bottom quality centers have 0 years above the sample average; top quality centers have all 8 years above the sample average; centers not at either extreme are grouped as middle quality. Column 1 uses 2012-2019 as the *Post* indicator; column 2 uses 2014-2019 as the *Post* indicator. Reference group is the top quality group. Both columns include other measures of quality, effort proxy variables, center characteristics, patient attributes, and year fixed-effects. Standard errors are derived using the two-step bootstrap procedure.

Overall, these results are intuitively consistent with Ramanarayanan and Snyder (2012), in that patients at bottom quality dialysis centers respond to the shock of learning about low quality

more than patients at middle or top quality dialysis centers. I graphically show this relationship in Figure 1.9, interacting all three quality types with year indicators. The statistical significance of this estimation is slightly lower than that of the *Post* indicator; the graph is displayed at the 90% confidence level instead of the traditional 95%. We observe a divergence in the probability of switching between 2012 and 2014, where patients at bottom quality dialysis centers increase the probability that they switch to a new provider. Patients at middle and top quality dialysis centers have a much smaller change in switching probability. In fact, the trend for patients at top quality centers is relatively flat between 2012 and 2017, suggesting that quality scores affirm their belief of high quality.

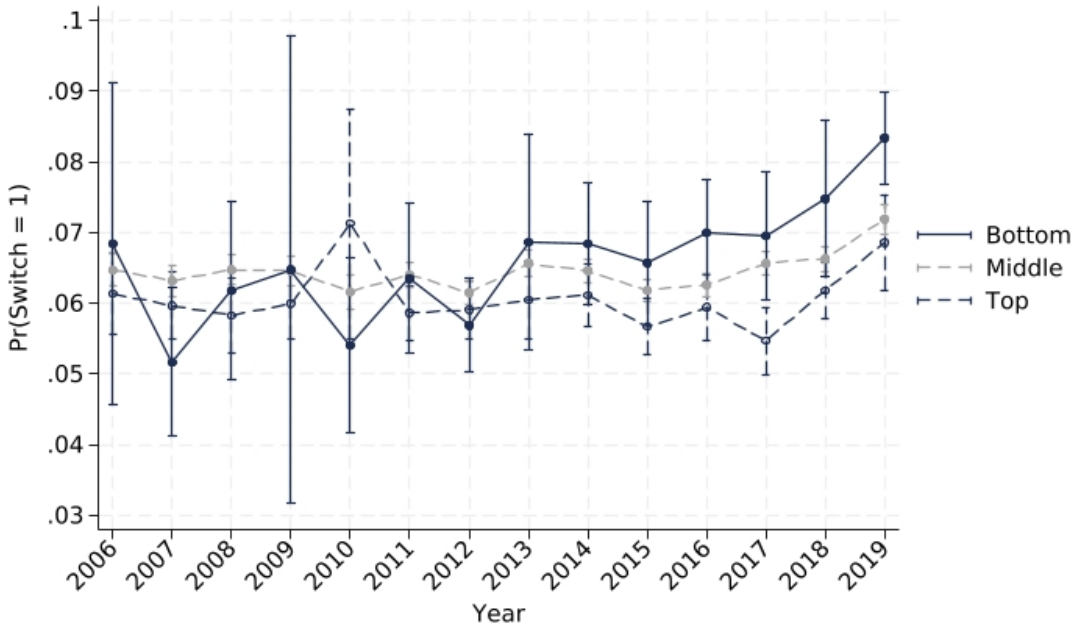



Figure 1.9 Probability of Changing Dialysis Centers by Quality Group
Notes: This figure shows the annual probability of switching for bottom, middle, and top quality dialysis centers. The solid circled line at the top are patients at dialysis centers in the lowest quality group. The middle dashed gray line are patients at dialysis centers in the middle quality group. The bottom dark dotted line at the bottom are patients at the highest quality dialysis centers. Standard errors are derived using the bootstrap procedure. Standard errors between the top and bottom quality centers do not overlap starting in 2016.

### 1.5.5 Predicted Quality Scores

Using average quality scores and the progression of quality scores between 2012 and 2019 both rely on the assumption that quality does not change dramatically over time. I relax this assumption and infer quality prior to 2012 by estimating predicted quality scores using data that is available in all years. This method presents a dynamic quality indicator that reflects changes at the dialysis center level each year. If a center is responding to unobserved factors that influence quality, then the predicted quality scores will capture this change, allowing dialysis centers to improve or worsen over time.

For 2014-2019, published quality scores are regressed on observed and expected values used to estimate both risk ratios, as well as dialysis center characteristics, such as annual patient hospitalizations and mortality rates. I omit the years 2012 and 2013 because these quality scores are only out of 30 and exhibit minimal variation. Using this model, I predict quality scores for the years 2006-2013. The estimating equation for predicted scores takes the form:

$$\begin{aligned} QIP_{jt} =& \alpha + \beta_{jt}^{kObs} \sum_{k} Observed^{k} + \beta_{jt}^{kExp} \sum_{k} Expected^{k} + \\ & \beta_{jt}^{Hosp} Hospitalizations_{jt} + \beta_{jt}^{Mort} Mortality_{jt} + \tau + \varepsilon_{jt} \end{aligned} \tag{1.9}$$

where $k$ is an indicator for *dialysis adequacy* or *infection rates*. The independent variables directly used to predict quality scores, except year fixed effects, are omitted from the main estimation. I use the time period from 2014-2019 as the treated period, following the same intuition as the previous section. I estimate fitted values $\widehat{QIP}_{jt}$ for each center-year. Additionally, I calculate a standardized quality score in each year with a mean of zero and standard deviation on one, as well as quartiles of predicted quality in each year. I then use the predicted quality scores in the following model:

$$\begin{aligned} P(Switch_{ijt} = 1 | \widehat{\mathbf{Q}}, \mathbf{C}, \mathbf{X}) =& \beta_0 + \beta_{jt} \widehat{\mathbf{Q}}_{jt} + \delta_0 \textit{Post2013} + \delta_{jt} \widehat{\mathbf{Q}}_{jt} \textit{Post2013} + \\ & \gamma_{jt} \mathbf{C}_{jt} + \theta_{it} \mathbf{X}_{it} \end{aligned} \tag{1.10}$$

Both alternative measures of quality, the dialysis adequacy and infection risk ratios, remain part of the dialysis center characteristics vector and are not interacted with the *Post* indicator. I

estimate the standard errors using the same bootstrapping procedure from the previous section and also include estimating the predicted quality. For the years 2006-2019, the predicted quality scores have a mean of 73.98 and a standard deviation of 6.77.

These results are shown in Table 1.11. Column 1 shows the estimation using the level of predicted quality. Column 2 uses the standardized quality score with a mean of zero and standard deviation of one, while column 3 uses the quartile of predicted quality. After 2013, predicted quality and switching are negatively related: when scores are published, a patient at a dialysis center with a predicted quality score one point higher is 0.07 percentage points less likely to switch. This effect represents nearly a threefold increase compared to the estimates based on average quality, as shown in Tables 1.8 and 1.9. The standardized quality score shows a similar response: patients at a dialysis center with a predicted quality score one standard deviation higher are 0.155 percentage points less likely to switch when scores are published. Similarly, patients at dialysis centers in higher quartiles are less likely to switch once they learn about quality. For example, a patient in the $4^{th}$ quartile of predicted quality is 0.2683 percentage points less likely to switch compared to those at centers in the $1^{st}$ quartile of predicted quality. These results suggest that dialysis patients are changing their behavior when they learn about quality, and moving away from lower quality dialysis centers.

Table 1.11 Predicted Quality and Switching
Years 2006-2019

| Pr(Switch=1) | (1) Predicted QIP Level | (2) Predicted QIP Standardized | (3) Predicted QIP Quartile |
|---|---|---|---|
| **Predicted Quality** | | | |
| (Predicted Quality)*Post | -0.0691*** | -0.1557** | |
| | (0.0214) | (0.0608) | |
| (Quartile 2)*Post | | | -0.0126 |
| | | | (0.1438) |
| (Quartile 3)*Post | | | -0.1783 |
| | | | (0.1492) |
| (Quartile 4)*Post | | | -0.2683* |
| | | | (0.1510) |
| Predicted Quality | -0.0083 | -0.0123 | |
| | (0.0179) | (0.0589) | |
| Post 2013 | 5.461*** | 0.8162*** | 0.9324*** |
| | (1.4711) | (0.1479) | (0.1768) |
| Quartile = 2 | | | -0.1245 |
| | | | (0.1097) |
| Quartile = 3 | | | 0.0455 |
| | | | (0.1234) |
| Quartile = 4 | | | 0.0363 |
| | | | (0.1394) |
| Observations | 3,033,210 | 3,033,210 | 3,033,210 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents estimates using predicted quality scores to infer quality prior to 2014. The first column uses the level of predicted quality interacted with a post-2013 indicator. The second column uses a standardized predicted quality score with a mean of zero and a standard deviation of one. The third column divides predicted quality into annual quartiles. The first quartile is the reference group and represents dialysis centers with the lowest predicted quality scores. Predicted quality scores are calculated by using data from 2014 through 2019 to estimate published quality scores. These estimates are then used to find the predicted values for 2006 through 2013. Covariates used to predict published quality scores are not included in the main estimation. Standard errors are estimated using the two-step bootstrap procedure.

### 1.5.6 Response to Dialysis Adequacy and Infection Risk Ratios

Dialysis patients may be responding to other measures of quality, and inferring quality before 2014 using scores after 2014 may be capturing these responses. I test whether patients are responsive to quality measures in general by estimating Equation 1.7 and interacting the risk ratios with the *Post* indicator for the years after 2014. The interaction term of *Post* with risk-adjusted ratios shows whether dialysis patients alter their response to these measures of quality following the publication of scores.

These results are presented in Table 1.12. In the first column, I include both risk adjusted ratios without an interaction with *Post*. The second column interacts the dialysis adequacy risk ratio with the *Post* indicator, and the third column interacts the infection rate risk ratio with the *Post* indicator. The last column interacts both risk ratios with the *Post* variable. All four estimations use the preferred specification from Table 1.6.

Both risk adjusted ratios are statistically significant throughout the study period. As shown in Column 1, a dialysis center with a 10% higher dialysis adequacy rate than expected is associated with a 0.102 percentage point decrease in the likelihood of switching. A 10% higher infection rate than expected is associated with a 0.051 percentage point increase in the probability of switching. When scores are published, patients exhibit a more pronounced response to the dialysis adequacy risk ratio, decreasing their switching probability by 0.250 percentage points. This could be due to the dialysis adequacy (urea reduction ratio and KtV) playing an important role in the calculation of performance scores. There is no measurable change with respect to the infection rate risk ratio once scores are published, as shown in column three. Interacting both risk ratios with the *Post* indicator does not change in the interpretation.

Table 1.12 Risk-Adjusted Quality Ratios
Data from 2006-2019

| Pr(Switch=1) | (1) Pooled | (2) Dialysis Adequacy | (3) Infection Rate | (4) Both |
|---|---|---|---|---|
| **Quality** | | | | |
| (Adequacy RR)*(Post) | | -0.250*** | | -0.245*** |
| | | (0.051) | | (0.050) |
| (Infection RR)*(Post) | | | 0.020 | 0.010 |
| | | | (0.015) | (0.015) |
| Post 2014 | | 0.335*** | 0.061*** | 0.319*** |
| | | (0.055) | (0.020) | (0.056) |
| Dialysis Adequacy | -0.102*** | -0.029 | -0.103*** | -0.031 |
| | (0.024) | (0.026) | (0.024) | (0.026) |
| Infection Rate | 0.051*** | 0.050*** | 0.040*** | 0.044*** |
| | (0.008) | (0.008) | (0.010) | (0.010) |
| Observations | 3,033,209 | 3,033,209 | 3,033,209 | 3,033,209 |
| R-squared | 0.028 | 0.028 | 0.028 | 0.028 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: Estimated likelihood of switching as a function of risk adjusted dialysis adequacy ratio and risk adjusted infection ratio using data from 2006-2019. Column 1 does not include an interaction term and shows the pooled effect of both ratios. Column two interacts risk-adjusted dialysis adequacy ratio with a post-2013 indicator variable but does not interact the risk-adjusted infection ratio. Column 3 moves the interaction to the risk-adjusted infection ratio. Column 4 interacts both the dialysis adequacy risk ratio and the infection rate risk ratio with the post-2013 indicator. All estimations include effort proxy variables, provider characteristics, patient attributes, and time fixed-effects. Standard errors are derived using the two-step bootstrap procedure.

I show the elasticity and the $10^{th}$ and $90^{th}$ percentile probabilities of switching as a function of risk ratios in Table 1.13. In the first column, a 10% increase in the dialysis adequacy risk ratio has minimal effect before 2014, but decreases the probability of switching by 6.17 percent after 2014. Going from the $10^{th}$ percentile to $90^{th}$ percentile before 2014 decreases the probability of switching by 0.09 percentage points (7.16 to 7.07), but after 2014, this difference is 0.89 percentage points, decreasing from 5.05 to 4.16 percent. In the second column, the elasticity of the infection rate risk ratio is 0.724 prior to 2014 and 1.049 after 2014, indicating that a 10% increase in the observed infection rate over the expected infection rate increases the likelihood of switching by

about 1%. Before 2014, patients at the $10^{th}$ and $90^{th}$ percentiles switch at a rate of 5.54% and 5.99%, respectively. After 2014, this increases slightly to 5.65% and 6.32%, respectively. Overall, Table 1.13 suggests that patients are using a center's dialysis adequacy risk ratio after 2014 once scores are released. The infection rate ratio also affects the likelihood of switching, but the increase in importance is much less pronounced than the dialysis adequacy risk ratio.

Table 1.13 Risk-Adjusted Quality Ratio Elasticity
Data from 2006-2019

| Pr(Switch=1) | (1) RA Adequacy Ratio | (2) RA Infection Rate |
|---|---|---|
| **Elasticity** | | |
| Pre | -0.409 | 0.724*** |
| | (0.383) | (0.177) |
| Post | -6.170*** | 1.049*** |
| | (1.324) | (0.199) |
| **10th Percentile** | | |
| Pre | 7.16 | 5.54 |
| Post | 5.05 | 5.64 |
| **90th Percentile** | | |
| Pre | 7.07 | 5.99 |
| Post | 4.16 | 6.32 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Note: Elasticity estimations from Columns (2) and (3) in Table 1.12. Only the risk ratio of interest is interacted with the post indicator. Estimations include dialysis center risk adjusted ratios, effort proxy variables, provider characteristics, patient attributes, and time fixed-effects. Standard errors are estimated using the two-step bootstrapping procedure.

These results provide mixed evidence that dialysis patients respond to new information about other quality measures. On the one hand, the magnitude of response to dialysis adequacy increases after scores are released, which could be due to dialysis adequacy having a prominent role in calculating quality scores. The dialysis adequacy risk ratio could be a valid proxy for published quality scores prior to 2014, so the change in behavior could be indicative of the response to

published quality. I explore this and further relaxing the static quality assumption in Appendix A.5 by comparing the quartiles of average quality to the quartiles of predicted quality and the dialysis adequacy risk ratio. On the other hand, the effect of the infection risk ratio does not influence a patient's decision differently once scores are published, indicating that patients may not be responding to other changes in quality after the publication of scores.

## 1.6 Destination Center and Heterogeneous Response to Quality

### 1.6.1 Switching Destination

Patients that choose to switch away from their current provider also choose a new provider. In this section, I consider the characteristics of these destination dialysis centers and how their quality might influence a patient's choice. I begin by showing the changes in the quality score and travel distance a patient experiences when they switch. I expand the scope to include the dialysis centers a switcher passes on. Last, I consider both switchers and non-switchers by modeling a simple discrete choice framework.

In Section 1.5, I show that dialysis patients are more likely to switch away from low quality dialysis centers. After 2013,[22] the destination quality scores for switchers are approximately 0.26 points higher than origin scores, with a correlation of 0.51. Patients add an average of 0.5 miles when they switch to a new provider, with a correlation of 0.33. In Table 1.14, I divide the sample into those that switch to a new dialysis provider that is strictly worse and further, worse and closer, better and further, and better and closer. In the first and second rows, I show the percent of switchers and the number of switchers that fall into each category. Row three shows the difference between the new and old quality scores, and row four shows the difference in the median travel distance.

[22]Recall that years 2012 and 2013 have minimal variation in quality scores, and most dialysis centers score the maximum value of 30.

Table 1.14 Destination Characteristics
Years 2014-2019

| % of Sample | Worse/Further | Worse/Closer | Better/Further | Better/Closer |
|---|---|---|---|---|
| Percent of Switchers | 25.48% | 23.71% | 24.72% | 26.09% |
| Number of Switchers | 14,634 | 13,618 | 14,197 | 14,985 |
| (New - Old) Score | -12.99 | -12.20 | 12.04 | 12.71 |
| (New - Old) Distance, Median | 4.73 | -3.91 | 4.37 | -4.10 |

Notes: This table presents basic summary statistics for the destination dialysis center for the years between 2014 and 2019. The years 2012 and 2013 are omitted due to the score being out of 30 and, in the case of 2013, very little variation in quality scores.

About 25.48% of switchers go to a worse dialysis center further away, and 26.09% go to a better center that is closer, representing a difference of about 350 switchers. Patients switching to a worse dialysis center experience the largest decline in quality scores if they switch to a further dialysis center, -12.99 to -12.20. Comparatively, those that switch to a better dialysis center experience a larger score improvement if they choose a closer center, 12.71 to 12.04. In terms of travel distance, those that choose a further dialysis center have the largest increase in distance if they go to a worse provider, 4.73 to 4.37 miles. Those that choose a closer provider have the largest decrease in distance if they choose a better provider, -4.10 to -3.91 miles.

In Table 1.15, I show some summary statistics in the year a patient switches. Pooled summary statistics are presented in the first column, and includes patients that switch to a worse, equal, or better dialysis center. The second column considers patients switching to a new provider with a strictly lower score in the same year, and the third column shows switchers going to a strictly higher scoring dialysis center. There are some notable features in Table 1.15. White non-Hispanic patients are more likely to switch to a better center, while Black patients are more likely to switch to a worse center. Interestingly, there are virtually no differences in insurance coverage between the two groups of patients, suggesting that privately and publicly insured patients switch to similar providers. Patients switching to a worse provider are slightly less healthy, with higher hospitalizations and infection rates, as well as a lower likelihood of surviving to the end of the sample period, December 31st, 2019.

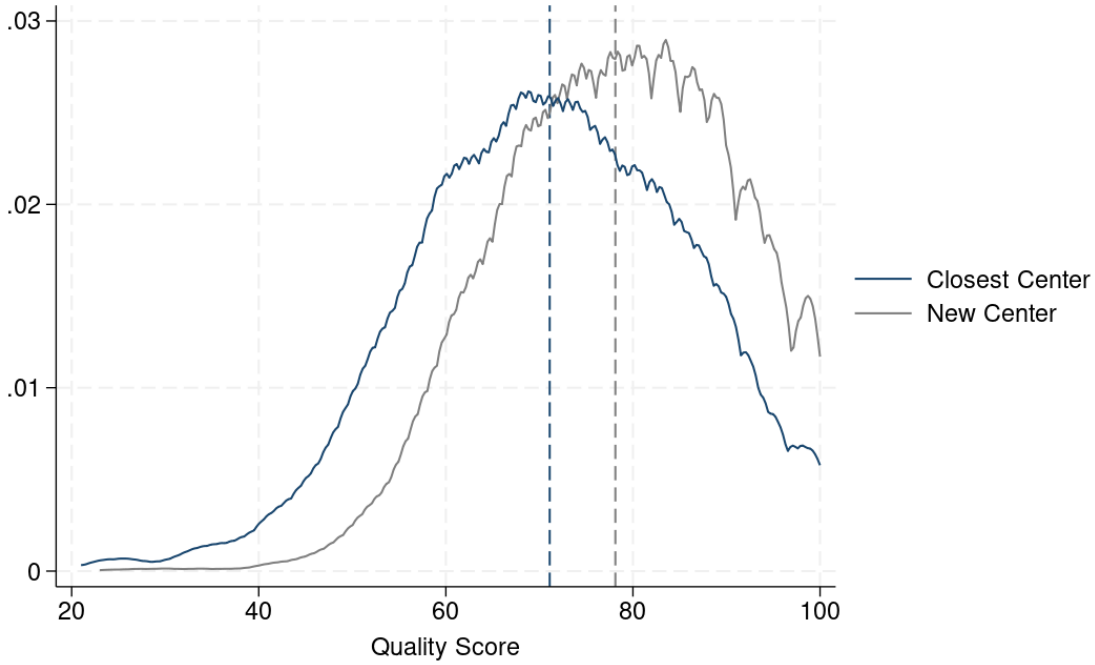
Table 1.15 Patient Characteristics by Relative Destination Quality
Years 2014-2019

| | All Destinations | Worse Destination | Better Destination |
|---|---|---|---|
| **Demographics** | | | |
| Age | 59.69 | 59.78 | 59.64 |
| Male | 57.44 | 57.14 | 57.66 |
| White, Non-Hispanic | 35.91 | 35.46 | 36.37 |
| Black | 39.91 | 40.22 | 39.69 |
| Asian | 3.66 | 3.67 | 3.62 |
| Other Race | 3.42 | 3.42 | 3.40 |
| Hispanic | 17.86 | 18.00 | 17.67 |
| Employed at Dialysis Start | 12.87 | 13.01 | 12.72 |
| Years on Dialysis | 4.35 | 4.41 | 4.30 |
| **Insurance** | | | |
| Any Medicare | 85.69 | 85.81 | 85.58 |
| Medicare | 66.70 | 66.82 | 66.45 |
| Medicare Advantage | 15.09 | 15.16 | 15.17 |
| Private Insurance | 4.75 | 4.72 | 4.76 |
| Other Insurance | 13.47 | 13.30 | 13.62 |
| Medicaid | 32.99 | 32.96 | 33.07 |
| Years on Dialysis | 4.35 | 4.41 | 4.30 |
| **Comorbidities** | | | |
| Congestive Heart Failure | 23.19 | 23.15 | 23.28 |
| COPD | 5.68 | 5.75 | 5.65 |
| Diabetic | 55.03 | 55.08 | 54.99 |
| High Blood Pressure | 89.81 | 90.00 | 89.67 |
| Stroke | 7.37 | 7.55 | 7.26 |
| Has Nephrologist | 68.74 | 69.08 | 68.49 |
| Primary Cause: Diabetes | 47.09 | 47.32 | 46.87 |
| Primary Cause: High BP | 30.32 | 30.22 | 30.47 |
| Needs Assistant w/ ADL | 8.37 | 8.22 | 8.55 |
| Glomerular Filtration Rate | 8.83 | 8.77 | 8.88 |
| BMI | 30.37 | 30.38 | 30.35 |
| **Health Outcomes** | | | |
| Dialysis Adequacy | 94.78 | 94.86 | 94.65 |
| Hospitalizations | 1.76 | 1.80 | 1.73 |
| Infection Rate | 12.15 | 12.56 | 11.81 |
| Never Dies | 64.95 | 64.35 | 65.95 |
| Observations | 106,281 | 49,707 | 51,938 |

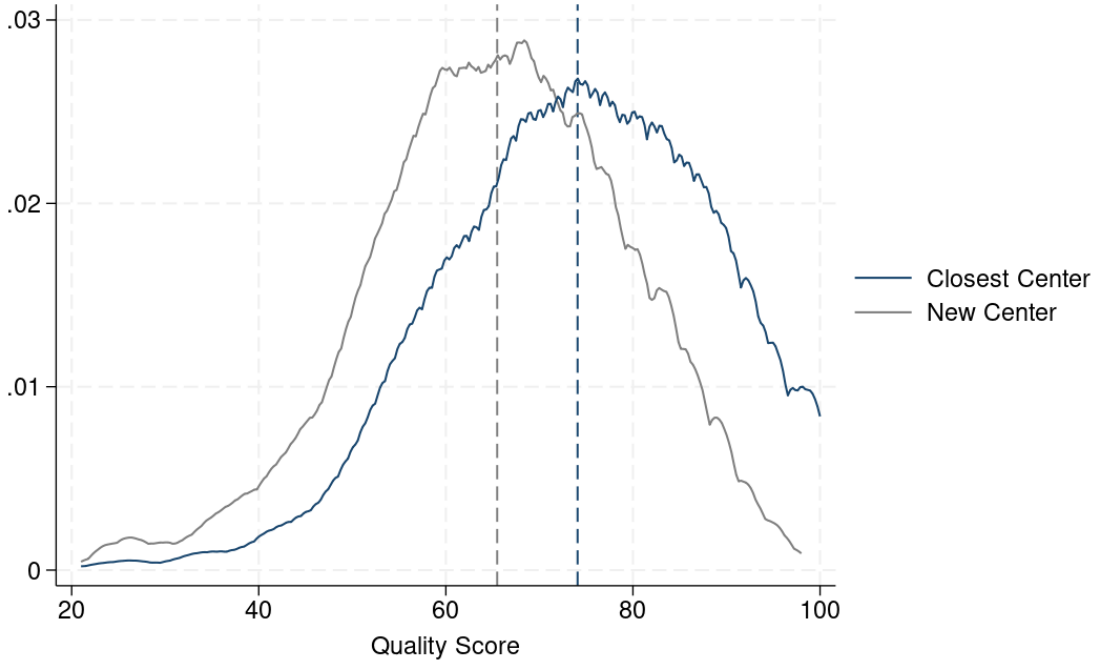
Notes: This table presents basic summary statistics for the destination dialysis center for the years between 2014 and 2019. The first column includes patients that switch a strictly worse, equal, or better dialysis center. The years 2012 and 2013 are omitted due to the score being out of 30 and, in the case of 2013, very little variation in quality scores.

Next, I consider the dialysis centers a patient passes on when they switch to a new center; that is, the dialysis centers a patient "drives by" to reach their new center. It could be the case that patients switch to low performing centers to avoid even lower quality alternatives. To see if this is the case, suppose a patient chooses the $n^{th}$ closest dialysis provider, while passing on $k \in \{1, 2, \ldots, n-1\}$ dialysis centers that are strictly closer. Let $\overline{Q}^k = \frac{1}{n-1} \sum_{i=1}^{n-1} Q_i$ be the average score for all $n-1$ dialysis centers a patient passes on when choosing dialysis center $n$. For example, if a patient chooses the $6^th$ closest provider, $\overline{Q}^k$ would be the average score of the $1^st$ through $5^th$ closest providers.

I plot quality score distributions in Figure 1.10 for two types of switchers: those that switch to a strictly better and those that switch to a strictly worse dialysis center. In each plot, I include the quality score of chosen provider and the quality score of closest dialysis center, with the requirement that they are not the same. Including a broader set of alternatives does not meaningfully change the distribution. Patients that switch to a new dialysis center with a quality score higher than their original dialysis center are shown in Panel 1.10a, and those that switch to a lower scoring center are shown in Panel 1.10b. The dark line represents the quality score distribution of the closest dialysis provider, and the lighter line represents the quality score distribution of the chosen dialysis provider.




(a) Better Distribution




(b) Worse Distribution

Figure 1.10 Distribution of New and Passed Dialysis Center Scores

Notes: Distribution of quality scores for the chosen (gray) and the closest alternative (navy) dialysis centers. The average of each distribution is represented by the dotted line. Patients switching to a better dialysis center are in the top panel, and those switching to a worse dialysis center are in the bottom panel. The scores in 2012 and 2013 are omitted due to scores being out of 30 instead of 100.

Patients that switch to a better dialysis center (Panel 1.10a) have a distribution that is shifted to the right of their closest alternative, with means of 78.12 and 71.10, respectively. This implies that patients switching to better centers are choosing a new dialysis center that is also better than the alternatives, on average. Conversely, patients that switch to a worse dialysis center (Panel 1.10b) have a distribution shifted to the left of their closest alternative, with average scores of 65.48 and 74.08, respectively. It does not appear to be the case that patients are choosing their new dialysis center to avoid an even lower scoring alternative: these patients could have chosen a higher scoring dialysis center closer to home, but chose a lower scoring and further provider.

I now consider the effect of other dialysis center scores on a patient's likelihood of switching. Do patients internalize other quality scores when making their decision to switch, or are they focused solely on their current provider's score? I simplify the choice set by only considering a patient's closest dialysis provider, the average score of the five closest, and the average score of the ten closest providers. I estimate the following equation, progressively adding each alternative score:

$$P(Switch_{ijt} = 1|\mathbf{Q, C, X}) = \beta_0 + \alpha_{j1t} f(Q_{jt}, \overline{Q}^1_{1t}) + \alpha_{j5t} f(Q_{jt}, \overline{Q}^5_t) + \alpha_{j10t} f(Q_{jt}, \overline{Q}^{10}_t) + \gamma_{it}\mathbf{C}_{jt} + \theta_{it}\mathbf{X}_{it} \tag{1.11}$$

where $f(Q_{jt},\ \cdot)$ is a function of the current dialysis provider's quality score and the average quality score of the closest, five closest, and ten closest dialysis centers. I operationalize this function by including the level and interaction of both the origin and alternative dialysis centers.

I show the results of this estimation in Table 1.16, focusing on the elasticity of the quality scores. The coefficients represent the percent-change in the likelihood of switching with a 10% increase in the quality score, calculated at the average value of the explanatory variables. In the first column, I consider the interaction between the current dialysis center and the closest dialysis center to a patient's residence. In the second column, I add the average score of the five closest, and in the third column I add the average score of the ten closest.

Table 1.16 Quality Score Elasticity of Alternative Dialysis Centers

| Pr(Switch=1) | (1) Closest Alternative | (2) 5 Closest Alternatives | (3) 10 Closest Alternatives |
|---|---|---|---|
| Origin Quality Score | -1.689*** | -1.990*** | -2.152*** |
| *(10%/% change)* | (0.417) | (0.471) | (0.496) |
| Avg. Closest | 0.721** | 1.119*** | 1.143*** |
| | (0.305) | (0.342) | (0.345) |
| Avg. 5 Closest | | -1.134 | -1.191 |
| | | (0.691) | (0.950) |
| Avg. 10 Closest | | | 0.294 |
| | | | (1.242) |

Notes: An observation is a patient-center-year. The dependent variable is the likelihood of a patient switching away from their current dialysis provider. Control variables are from the origin dialysis center, and include those from column 6 in Table 1.6. Standard errors are clustered at the dialysis center level.

In all three columns, the quality score of the current dialysis provider is negative, which is consistent with Table 1.7, although the effect is slightly smaller. In the first column, the elasticity of the closest alternative is 0.721, indicating that increasing the quality score of the closest alternative increases the likelihood of switching by 0.721% at the average value of the current quality score. The effect increases slightly when considering the five and ten closest centers, to 1.119 and 1.143, respectively. The second and third columns indicate that patients do not consider the five closest and ten closest dialysis centers. Overall, Table 1.16 suggests that patients primarily use the quality score of their closest dialysis provider and current dialysis provider when deciding to switch. While the scores of further alternatives may be important, the influx of information may be too noisy to make a difference for most patients.

### 1.6.2 Dialysis Center Choice

Patients may not use the quality scores of alternative dialysis centers when deciding to switch, but the scores may nonetheless be useful when determining which dialysis center to choose. I test whether this is the case by setting up and estimating a conditional logit model. The conditional logit hinges on the independence of irrelevant alternatives (IIA) assumption, and assumes the

errors follow a type I extreme value distribution (McFadden, 1972). Under the IIA assumption,[23] the correlation between alternatives is assumed to be zero.

Let the utility of patient $i$ considering dialysis center $k$ be written as

$$U_{ik} = \beta x_{ik} + \varepsilon_{ni} \tag{1.12}$$

where $x_{ik}$ is a vector of characteristics for dialysis center $k$, which includes travel distance and dialysis center quality, and $\varepsilon_{ik}$ is assumed i.i.d. extreme value. The choice probabilities can then be expressed as

$$P_{ikt} = \frac{e^{\beta X_{ik}}}{\sum_j e^{\beta X_{ij}}} \tag{1.13}$$

where $P_{ikt}$ is the probability that patient $i$ chooses dialysis center $k$ among $j$ alternatives. I restrict the patient's choice set to the 10 closest dialysis centers, which accounts for over 70% of chosen dialysis centers. Additionally, I omit the years 2012 and 2013 because of the minimal variation in quality scores. I show the results in Table 1.17. In the first column, I use the quality score and travel distance to the dialysis centers in a patients choice set. In the second column, I add additional characteristics of the choice set. These characteristics include both risk-ratios, the number of dialysis stations, staffing levels, profit status, and whether the dialysis center is Davita or Fresenius. Coefficients are presented as odds ratios.

[23] In healthcare discrete choice models, it is common to relax the IIA assumption and estimate a mixed-logit choice model (Pope, 2009). However, the trade-off between the computational burden and precision of the estimates is considerable. In my setting, I opt to keep as many cases as possible and sacrifice less precise estimates for convergence with the full sample.

Table 1.17 Discrete Choice

| Pr(Switch=1) | (1) Conditional | (2) Conditional |
|---|---|---|
| Quality Score | 1.0003** | 1.0023*** |
| | (0.0001) | (0.0002) |
| Travel Distance (mi) | 0.8241*** | 0.8267*** |
| | (0.0010) | (0.0011) |
| Risk Ratio: Adequate | | 1.3392*** |
| | | (0.0276) |
| Risk Ratio: Infection | | 1.0002 |
| | | (0.0046) |
| Dialysis Stations | | 1.0125*** |
| | | (0.0005) |
| High Certification Staff | | 0.9791*** |
| | | (0.0013) |
| FTE Staff | | 1.0371*** |
| | | (0.0008) |
| For Profit | | 1.0242** |
| | | (0.0121) |
| Davita | | 1.0645*** |
| | | (0.0086) |
| Fresenius | | 1.0581*** |
| | | (0.0087) |
| Cases | 757,141 | 540,763 |

Exponentiated coefficients; standard errors are clustered at the patient-level.
*** p<0.001, ** p<0.01, * p<0.05

Notes: This table shows the estimates from the conditional choice specification. Each observation represents a unique patient-center pair. Choices are limited to the nearest 10 dialysis centers. Years prior to 2014 are omitted.

In the first column, a higher quality score is associated with a higher likelihood of being chosen, although the effect is economically small: a 1 point increase in score is associated with a 0.03% higher odds of being chosen. The effect of travel distance is larger in magnitude: increasing the distance a patient would have to travel to reach a dialysis center decreases the odds of being chosen by about 17%. The effects are similar when we include additional center characteristics, as shown in the second column. Patients are more responsive a dialysis centers risk ratio for dialysis

adequacy compared to the risk ratio for an infection: 34% to 0.02%. Patients prefer more staff members, although they dislike higher certification staff. There is also a preference for for-profit centers and both Davita and Fresenius, although this could be because few dialysis centers are non-profit, and Davita and Fresenius dominate the market for dialysis. Overall, these results are consistent with the estimations from the previous section, in that patients prefer higher quality and a shorter travel distance.

I next explore the role of information salience in patient decision-making by repeating the same estimation but for the time periods before and after 2014, when the scores are first out of 100 and provide meaningful information for patients. Because quality scores are not available prior to 2012, I use the dialysis adequacy risk ratio, a quality measure that closely tracks quality scores from 2012-2019. I include the same variables from the second column of Table 1.17, but omit them for clarity. The results are shown in Table 1.18. Coefficients are exponentiated to show the odds-ratio. The first column represents the time period from 2006-2013, when scores are either not available, or only out of 30 and therefore do not provide meaningful variation. The second column represents the time period from 2014-2019 when scores are available.

Table 1.18 Quality Salience

| Pr(Switch=1) | (1) Pre-2014 | (2) Post-2014 |
|---|---|---|
| Travel Distance (mi) | 0.8289*** | 0.8244*** |
| | (0.0008) | (0.0009) |
| Risk Ratio: Adequate | 1.1600*** | 1.3799*** |
| | (0.0096) | (0.0179) |
| Cases | 1,513,259 | 1,037,884 |

Exponentiated coefficients; *t* statistics in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Notes: Each observation represents a unique patient-center pair. Choices are limited to the nearest 10 dialysis centers. The pre-2014 period includes 2006-2013, and the post-2014 period includes 2014-2019. Additional covariates included in the estimation are the infection rate risk ratio, the number of dialysis stations, the number of FTE staff and high certification staff, and ownership indicators. Standard errors are clustered at the patient-level.

In both columns, travel distance plays a prominent role in a patient's choice of dialysis center. The estimated odds-ratios are similar, at 0.8289 and 0.8244, respectively. Prior to 2014, the dialysis adequacy risk ratio is positively associated with a patients choice: increasing a dialysis center's risk ratio by 1% increases the odds of being chosen by 16%. The effect of a center's dialysis adequacy risk ratio is more than doubled starting in 2014, increasing from 16% to 38%. The increased effect suggests that patients are likely more responsive to dialysis center quality when scores are available.

### 1.6.3 Heterogeneous Response

How dialysis patients respond to the publication of quality scores and their overall response to quality may depend on individual patient characteristics. Recognizing these heterogeneous responses can provide valuable insights for improving the Quality Incentive Program. For example, older patients may not be as responsive to published quality scores due to concerns about mobility, while younger patients may face fewer health barriers when considering a change of dialysis center. Additionally, patients who have been on dialysis for a longer period of time may be less responsive

to published quality information due to market learning, where their belief about quality is stronger due to more experience at their dialysis center (Dafny and Dranove, 2008).

I test whether this is the case by repeating four of the previous estimations and presenting the results in Table 1.19. The first estimation in Panel A is the effect of the level of published quality on the likelihood of switching from 2012 through 2019, identical to Column (6) from Table 1.6. The second estimation in Panel B uses the average quality score from 2014-2019 and a post-2012 indicator, corresponding to Column (2) of Table 1.8. The third estimation in Panel C uses the average quality score from 2018-2019 and a post-2014 indicator, identical to Column (4) of Table 1.9. The final estimation in panel D uses the bottom, middle, and top quality classifications interacted with a post-2012 indicator, analogous to Column (2) of Table 1.10. In each estimation, I separately interact the quality score with ten binary variables: three race indicators for white, Hispanic, and black; an indicator for whether a patient is less than 65 years old; a gender indicator; whether a patient lives in an urban or rural setting; and whether the patient has been on dialysis for less than one year, at least one but less than two years, at least two but less than three years, or at least three years.

Table 1.19 Heterogeneous Response to Quality Scores

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Race | | | | | Years on Dialysis | | | |
| Model | White | Hispanic | Black | Under 65 | Male | Urban | 0-1 | 1-2 | 2-3 | 3+ |
| *Panel A:* **QIP Level** | | | | | | | | | | |
| | 0.001 | -0.005 | 0.003 | -0.003* | -0.002 | -0.004 | 0.004** | 0.001 | -0.001 | -0.003* |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.001) |
| *Panel B:* **(Avg QIP 2014-19)(Post)** | | | | | | | | | | |
| | 0.032*** | -0.015 | -0.023* | -0.023*** | -0.009 | -0.026 | 0.024** | 0.009 | 0.002 | -0.022*** |
| | (0.010) | (0.017) | (0.012) | (0.009) | (0.008) | (0.016) | (0.010) | (0.011) | (0.011) | (0.008) |
| *Panel C:* **(Avg QIP 2018-19)(Post 2014)** | | | | | | | | | | |
| | 0.025*** | -0.012 | -0.014 | -0.020*** | -0.009 | -0.034*** | 0.008 | 0.007 | 0.008 | -0.014** |
| | (0.008) | (0.014) | (0.009) | (0.006) | (0.006) | (0.012) | (0.008) | (0.009) | (0.009) | (0.006) |
| *Panel D:* **(Quality Group)(Post)** | | | | | | | | | | |
| Middle | -0.276 | 0.165 | -1.91** | 0.145 | 0.303 | -0.468 | -0.397 | 0.080 | -0.365 | -1.88 |
| | (0.292) | (0.408) | (0.646) | (0.212) | (0.215) | (0.346) | (0.310) | (0.307) | (0.659) | (0.459) |
| Top | -2.495*** | 0.766 | -1.794** | 0.450 | 0.565 | 0.208 | -2.838*** | -0.456 | -0.726 | -1.970*** |
| | (0.731) | (1.100) | (0.707) | (0.649) | (0.444) | (1.047) | (0.729) | (0.685) | (0.716) | (0.513) |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: Previous estimations are repeated but include an interaction between quality and the characteristic of interest. Panel A uses the level of quality scores; Panel B uses average quality from 2014-2019 and a post-2012 indicator, and Panel C uses 2018-2019 and a post-2014 indicator. Panel D uses the quality groups and a post-2012 indicator. All estimations use risk-adjusted ratios, effort proxy variables, provider characteristics, patient attributes, and time fixed-effects. Standard errors are clustered at the dialysis center level.

Overall, there is some response heterogeneity among different groups. White patients (Column 1) generally decrease the switching probability with higher quality scores compared to non-white patients, and Hispanic (Column 2) and black patients (Column 3) have more muted responses. Patients under the age of 65 (Column 4) have a stronger decrease in switching likelihood when quality is higher. It could be the case that younger patients can interpret scores better than older patients. Older patients may also rely on family members or non-emergency transportation services to travel to and from dialysis appointments, making switching more difficult. Continuing to Column (5), men and women do not have a differential response. We do observe a lower likelihood of switching with higher scores for patients in an urban setting (Column 6), but this is only the case in Panel C. Time on dialysis appears relevant only for patients who have been undergoing treatment

for less than one year (column 7) or those with at least three years of treatment (column 10).

## 1.7 Robustness

### 1.7.1 Provider Selection on Patients

One factor that may influence the estimate of quality scores on patient switching is the possibility that dialysis centers selectively choose their patients. Bertuzzi et al. (2023) shows that dialysis patients who would trigger a financial penalty are more likely to switch providers. Additionally, hospitalized patients are more likely to switch to a different dialysis provider, suggesting that dialysis centers may have some influence in whom they treat after adverse events (Bertuzzi et al., 2023). Dialysis centers may influence their patient roster by refusing treatment to current patients[24] or being selective in the patients that they accept to begin treatment. This practice, known as "cream skimming," occurs when a healthcare provider intentionally serves healthier patients to reduce the likelihood of an adverse event (Dranove et al., 2003; Chen and Sivey, 2021). If cream skimming is present, then some patient switching may be due to dialysis centers manipulating their patient roster, rather than patients responding to quality scores.

I test for the presence of patient selection by focusing on dialysis centers that would benefit from removing higher-risk patients. In 2014, CMS added vascular access as an input into the quality score. Because of the significant benefits of a fistula (Brown et al., 2017), dialysis centers receive a higher score for having more patients with a fistula and a lower score for having more patients with a catheter.[25] I analyze the annual switching rates for patients with and without a catheter. If dialysis centers are selective in their patient rosters, patients with catheters should be more likely to switch when the center is slightly above or slightly below the financial penalty threshold. These patients

[24]Removing a patient from the patient roster without their consent is deemed an "involuntary discharge" by CMS. An involuntary discharge can occur if the dialysis center is no longer reimbursed; if the center closes; if a transfer is necessary for the patient's welfare or medical need; or if the patient's behavior is disruptive and abusive (CMS, 2008). Dialysis centers certified by CMS and treating Medicare patients must have a valid reason to refuse treatment to a patient. Patients who are not treated for at least 30 days can be removed from the roster, a mechanism studied in Bertuzzi et al. (2023). A dialysis center can otherwise refuse to admit a patient if the patient's insurance is not accepted by the facility.

[25]A fistula is a surgically created connection between a vein and artery, while catheter is a flexible tube inserted into a large vein. Fistulas are much more durable, have fewer complications, and have a significantly lower associated mortality rate and risk of infection compared to catheters.

may alter the center's performance score enough to trigger a financial penalty. In contrast to the measures of dialysis adequacy used in Bertuzzi et al. (2023), vascular access is a binary variable that is immediately observable by the dialysis center, making it an ideal characteristic for patient selection.

I show the estimated trend of switching for patients at dialysis centers 10 points above and 10 points below the threshold for a financial penalty in Figure 1.11. The solid line represents patients with catheters, who may lower the center's quality score, while the dotted line represents patients without a catheter. Patients at a dialysis center not facing a financial penalty in year $t$, at least 10 points above the threshold, are shown in the left panel, and those at a center facing a financial penalty, no more than 10 points below the threshold in year $t$, are shown in the right panel.

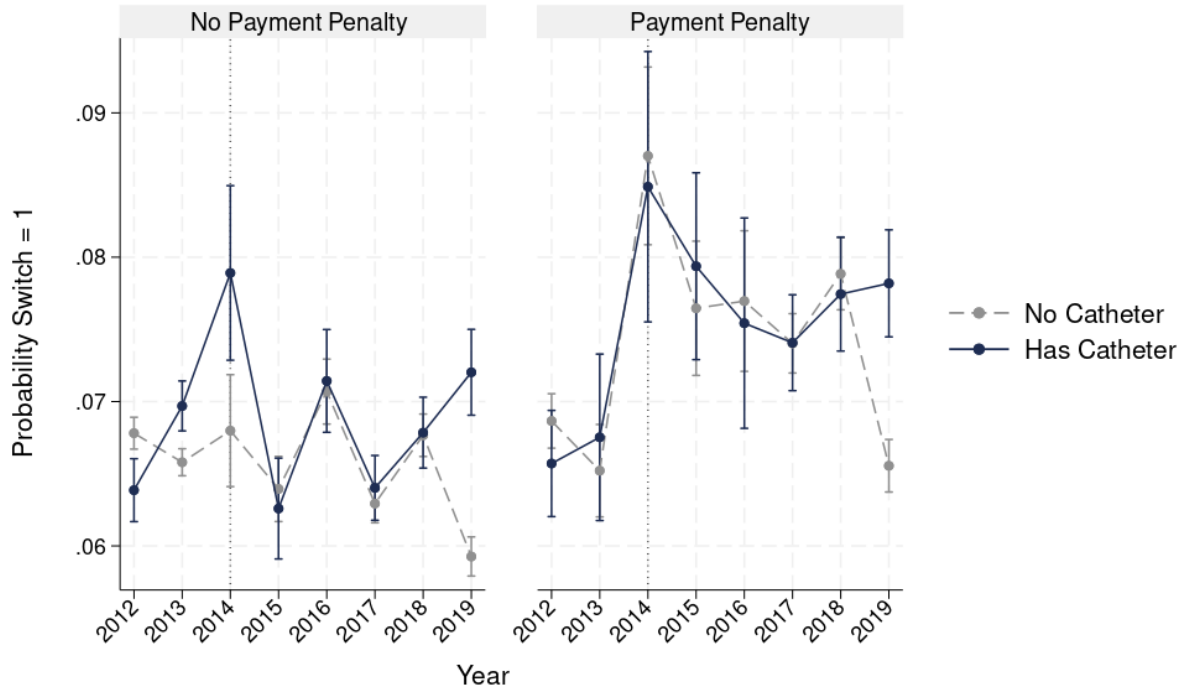



Figure 1.11 Effect of Vascular Access on the Probability of Changing Dialysis Centers
Notes: The probability of switching for patients with and without a catheter at dialysis centers that were and were not assessed a financial penalty for a low score.

There is some evidence suggesting that dialysis centers may influence their patient rosters, but this effect is small and short-lived. In 2013 and 2014, patients at dialysis centers slightly above the

payment penalty threshold are more likely to switch if they have a catheter, which is shown in the left panel of Figure 1.11. The difference in switching could be due to dialysis centers concerned about their score anticipating the change in 2013, and then reacting to the change in 2014. After 2014, the switching rates for both patient groups converge and become nearly identical. At dialysis centers that are assigned a payment penalty, patients with either a catheter or fistula have similar probabilities of switching, as shown in the right panel of Figure 1.11. Overall, these results suggest that dialysis centers could be influencing their patient roster in the earlier years of the program by inducing riskier patients to leave, but this effect does not persist beyond 2014 and appears to be temporary. Patient selection in my setting may not be a significant contributor to the likelihood a patient switches centers, although I cannot definitively rule out such behavior.

## 1.8 Conclusion

In 2012, the Centers for Medicare & Medicaid Services (CMS) initiated the End Stage Renal Disease Quality Incentive Program (QIP), publishing quality scores for dialysis centers to reduce information asymmetries between patients and providers. How patients use this information in their decision-making is unclear. I provide evidence that patients respond to these scores by changing the likelihood that they switch dialysis centers. Specifically, patients at dialysis centers with a published score in the $10^{th}$ percentile are 19% (1.1 percentage points) more likely to switch than those in the $90^{th}$ percentile. After scores become salient, patients at the lowest quality dialysis centers increase their likelihood of switching by 1.18 percentage points compared to those at the highest quality centers. These findings are robust to accounting for other indicators of dialysis center quality and travel distance, confirming that quality scores provide novel and meaningful information. This study demonstrates the responsiveness of dialysis patients to learning about quality, adding to a growing literature validating the efficacy of the Quality Incentive Program (Bertuzzi et al., 2023; Eliason, 2022; Eliason et al., 2024).

In the context of these results, there are several key policy implications. First, reducing information asymmetries through public reporting can significantly improve patient-provider matching, particularly when patients value quality. For dialysis patients, many of whom have tenuous health,

this improved matching can have substantial short- and long-term effects on health outcomes. By empowering patients to make more informed decisions about their dialysis center, the QIP can steer patients away from low-quality centers and improve health outcomes. Better matching can further improve resource allocation efficiency by directing reimbursement away from low quality dialysis centers, and by avoiding costly adverse health events. Furthermore, patient switching represents a direct threat to the revenue of low-quality dialysis centers, which may be more effective at incentivizing centers to improve quality than payment penalties alone (Sheetz et al., 2021),with spillover effects for all dialysis patients (Kepler et al., 2024).

Despite these benefits, challenges with the QIP remain. Patients may face difficulties accessing or interpreting quality scores, despite the requirement to prominently display quality scores at the center. Previous quality disclosure initiatives were largely unsuccessful due to the complexity of quality information (Trisolini et al., 2006), suggesting that providing easy to understand scores is essential to the success of the QIP. Additionally, without easy access to past performance data, patients may struggle to assess whether their center is improving or worsening over time. To address this, CMS could require centers to simultaneously display historic and current scores. Last, dialysis centers may try to game the QIP and improve their score by avoiding riskier patients (Bertuzzi et al., 2023). If patients are then switching for reasons unrelated to their interpretation of quality, this may undermine the goals of the program and negate many of the benefits. Risk-adjusting quality scores, as demonstrated in previous studies (Chen and Sivey, 2021), could mitigate this concern and lead to improved patient welfare.

CMS has already taken steps to address some of these concerns by introducing standardized readmission and transfusion ratios that account for patient risk factors. However, the continued success of the QIP depends on how effectively CMS adapts to changes in the dialysis landscape. The program must evolve to meet the increasing needs of the end stage renal disease community and ensure that patients remain responsive to quality information without sacrificing actual quality.

# CHAPTER 2

# PATIENT PREFERENCE OR PROVIDER INFLUENCE: VARIATION IN HEALTH CARE SPENDING AMONG DIALYSIS PATIENTS

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

## 2.1 Introduction

Health costs are one of the largest public expenditures in the United States and are projected to increase as a share of total GDP over the next decade (Fiore et al., 2024). Despite these high costs, evidence is mixed in whether these higher costs are associated with better health outcomes compared to other developed nations (Skinner, 2011). Understanding the drivers behind high healthcare costs and variations in spending is a crucial step to addressing inefficiencies in healthcare markets. If patients are responsible for high levels of healthcare utilization, then the most effective policies will target demand-side factors, such as compliance to medications or the accessibility of healthcare services. Conversely, if providers and hospitals are the primary causes of high spending, then demand-side policies will be ineffective at lowering costs.

In this paper, I study the components of healthcare spending for patients undergoing dialysis treatment to treat end stage renal disease (ESRD). Patients with ESRD qualify for full Medicare coverage, and represent about 1% of all Medicare patients but account for over 7% of all Medicare spending (U.S. Renal Data System, 2023). CMS spends about $80,000 per ESRD patient per year: $40,000 of which goes towards dialysis treatment specifically, with the remaining $40,000 being spent on non-dialysis related healthcare. With high amounts of health utilization, understanding and addressing variations in spending between dialysis patients could result in substantial savings.

Dialysis treatment centers are uniquely positioned to influence patient utilization. Because treatment must occur three times per week and patients tend to use the same dialysis center for all treatments (Grieco and Mcdevitt, 2017; Eliason et al., 2020), patients have a consistent source of health information and reliable interactions with healthcare providers. Patients may, for example, be

exposed to more or less aggressive campaigns for influenza vaccinations, or be regularly encouraged to visit their primary care provider (PCP) for aches and pains.

I use patient switches to identify provider effects on patient utilization. I borrow from similar works that use patient movers to identify the effects of geography on variations in healthcare spending (Finkelstein et al., 2016; Godøy and Huitfeldt, 2020; Badinski et al., 2023) and mortality (Deryugina and Molitor, 2020; Finkelstein et al., 2021), as well as physician movers to identify the effects of different practice styles on patient outcomes (Fadlon and Parys, 2020; Badinski et al., 2023) and treatment intensity (Molitor, 2018). In these models, patients live in a defined geographic region or use a specific physician as their primary care provider. They are exposed to an origin utilization environment, defined as the utilization of other patients in the same area or under the care of the same physician. A patient then moves to a new area or switches to a new provider, and experiences a change in the utilization environment. The degree to which a patient's own spending or health conforms to that of their new utilization environment provides insight into place or provider effects. If these effects are small, then a patient's spending should not be affected by their new location or physician; if place or provider effects are large, then spending should converge to the average of their new location (Finkelstein et al., 2016; Fadlon and Parys, 2020) or new physician (Molitor, 2018; Huang and Ullrich, 2024).

In my setup, dialysis patients are assigned to an origin dialysis center $j$. The utilization environment is the average outcome for all patients at center $j$, such as total spending or hospitalizations. A patient then switches to dialysis center $j'$ and is exposed to a new utilization environment. I use the change in the utilization environment as a source of variation and track how a patient's own spending evolves. I consider patients that switch but do not move, thereby isolating changes brought on by a new utilization environment rather than a new geographic location (Finkelstein et al., 2021) or a new primary care provider (Fadlon and Parys, 2020).

While dialysis is mostly homogenous across dialysis centers, there is substantial heterogeneity in what patients experience. Different factors such as profit status and managerial decisions (Grieco and Mcdevitt, 2017), judicious use of certain medications (Eliason et al., 2024), and standard

operating procedures for infection control (Patel et al., 2013) can all influence patient outcomes. Dialysis centers may be more or less likely to speak with patients regarding options for kidney transplantation (Gander et al., 2019), and the number of dialysis treatments is strongly associated with hospitalization rates (Dalrymple et al., 2014). Additionally, Erickson et al. (2013) show that a patient's health status does not fully explain variation in nephrologist visits and suggests that facility location and characteristics may play a substantial role. Given the increased prevalence of kidney failure and a rapidly expanding dialysis industry (Eliason et al., 2020), dialysis provider heterogeneity could manifest through increased costs and substantial variation in utilization.

I begin my study by characterizing dialysis patients that are switchers and stayers. Switchers tend to be slightly younger and healthier, although they do have higher spending and use slightly fewer health services. Regardless, spending is high and variable across several categories, such as non-dialysis outpatient, in-patient, and physician/supplier services. In my sample, the average patient spends almost $39,000 on non-dialysis services, of which over $22,500 per year is on inpatient services, including hospitalizations and surgeries.

I then characterize the utilization at dialysis centers. Overall, patients are slightly more likely to switch into a higher (level) utilization dialysis center compared to their origin dialysis center. The difference in logs in my setting is in-line with Finkelstein et al. (2016) and Godøy and Huitfeldt (2020), both of whom find a difference in log-utilization symmetrically distributed around zero. I show that patients that switch to a relatively higher utilization dialysis center experience a larger change in their own spending, providing early suggestive evidence of provider effects.

Following prior work (Finkelstein et al., 2016; Godøy and Huitfeldt, 2020; Fadlon and Parys, 2020), the influence a dialysis center has on patient utilization is modeled as a standard event study. Under this specification, the change in utilization environment experienced from a switch is interacted with relative switch-year indicators. The interaction gives a dynamic estimate for how a patient's utilization changes in years before and after a switch, with varying degrees of a changing utilization environment. Similar to Finkelstein et al. (2016), the coefficients show the share of variation that is attributable to dialysis center heterogeneity. As a preview of my results, dialysis

patients experience an immediate and sustained change in utilization following a switch. Dialysis centers account for about 61% of the variation in total utilization. When controlling for whether a patient is hospitalized in a given year, the results decrease to 37.6% but remain statistically significant, suggesting that health status is an important factor when considering dialysis patient utilization.

These questions have important policy implications. Patients diagnosed with end-stage renal disease qualify for full Medicare coverage without any age requirement. In 2019, Medicare spending per beneficiary for all Medicare patients was estimated to be $14,100 (Insurance and Funds, 2023). For patients receiving hemodialysis, who are a subset of patients diagnosed with end-stage renal disease (ESRD), Medicare spending exceeded $80,000, with approximately half going towards dialysis services specifically and half going toward non-dialysis related care (U.S. Renal Data System, 2023). High variation in non-dialysis spending between patients at different dialysis centers can represent a substantial difference in spending. For example, my estimates suggest that dialysis centers account for approximately 63% of the variation in non-dialysis outpatient spending. A patient that switches to a dialysis center with non-dialysis outpatient spending one-standard deviation higher will increase their own spending by approximately $925. This represents nearly a 20% increase relative to average outpatient spending of $4,536.

These estimates suggest that policies targeting non-dialysis outcomes may be effective at reducing costs. For example, CMS could implement financial incentives for dialysis centers to reduce hospitalizations or readmissions. My estimates suggest that dialysis center heterogeneity accounts for 51.1% of the variation in hospitalizations. A patient switching to a new dialysis center with a hospitalization rate one-standard deviation lower will experience 0.20 fewer hospitalizations per year (0.427*0.51). Financially, this could reduce inpatient spending by (0.411*6,994) = $2,800. Similar incentives have been effective at incentivizing hospitals to reduce readmissions (Gupta, 2021). A targeted policy to penalize dialysis centers with excess hospitalizations could reduce costs by withholding reimbursement due to high hospitalizations and from the direct savings from 0.20 fewer hospitalizations. While CMS has taken steps to address increasing dialysis-related costs

through the End Stage Renal Disease Quality Incentive Program (Reaves and Weiner, 2021; Kepler et al., 2024), addressing dialysis center heterogeneity could be another mechanism to rein in costs and improve patient outcomes, without sacrificing patient wellbeing.

This paper contributes to two areas of research. First, a robust body of work uses changes or differences in environment to estimate the effects on patient utilization and outcomes. Migration is a common mechanism to study place-effects on patient health. Finkelstein et al. (2016) use Medicare movers to identify geographic variation in healthcare spending. They find that roughly 40-50 percent of variation in healthcare utilization is due to patient demand, with the remainder due to supply-side factors. Godøy and Huitfeldt (2020) explore a similar mechanism using Norwegian data and show that the magnitude of change depends on whether patients migrate to a relatively higher or lower utilization region. Salm and Wübker (2020) identifies patient- and place-effects on ambulatory care utilization in Germany. In contrast to previous works, they find that patient-effects have a much larger influence than place-effects, reflecting the regulatory environment around healthcare access and reimbursement (Salm and Wübker, 2020). Deryugina and Molitor (2020) exploit migration due to Hurricane Katrina to identify the effects of changing geography on mortality, finding substantial gains when patients move to a region with a lower mortality rate.

Other works have used changes involving the physician to identify patient- and provider-effects. Fadlon and Parys (2020) estimate that changing a patient's primary care provider through a physician's retirement or relocation drastically influences utilization and the number of diagnosed conditions. Huang and Ullrich (2024) use physician exits to identify the effects of provider practice styles on antibiotic prescribing practices, finding that practice style heterogeneity accounts for nearly 50% of the difference in overall antibiotic use. Molitor (2018) exploit physician migration to study how changing geography affects cardiologists' treatment intensity of heart attacks. Using an event-study to implicitly test for the assumptions needed for a difference-in-difference, they find a point estimate of 0.63, indicating that a 1 percent increase in treatment-intensity environment increases a physician's own treatment intensity by 0.63 percent. Badinski et al. (2023) studies the role of physicians in geographic variation in health care using physician and patient migrants,

finding that about one-third of geographic differences in health care utilization are due to physician treatment heterogeneity. Outside of health, migration has been used to study the effects of firm and worker heterogeneity on employee wages (Card et al., 2013), explaining earnings dispersion on workers sorting to firms (Bonhomme et al., 2019), and differences in voting behavior (Cantoni and Pons, 2022).

Other work uses difference in treatment intensity without migration. Currie et al. (2016) exploits differences in cardiologists' likelihood to perform invasive procedures to study patient outcomes and costs. To study birth outcomes, Card et al. (2023) use variations in C-section rates between comparable hospitals. Doyle et al. (2010) shows that patients treated by physicians at a higher ranked hospital have lower costs and better outcomes, and Doyle et al. (2015) suggests that hospitals with higher Medicare reimbursement have better emergency department mortality rates. My contribution to these works is by using patient switching, rather than migration or random assignment to physicians and hospitals, to identify provider effects. Additionally, I study dialysis patients, a relatively understudied patient population that accounts for a substantial portion of Medicare spending.

The second contribution of this paper is to a growing body of work to understand dynamics of dialysis markets and dialysis patients. Grieco and Mcdevitt (2017) suggests that dialysis centers face a quality-quantity trade-off: in the short-run, a center can treat fewer patients with high quality dialysis or treat more patients with low quality dialysis. Eliason (2022) further explores the quality decision in the presence of price regulation, while Eliason et al. (2020) show how a dialysis center's practice style evolves following an acquisition. Kepler et al. (2024) estimates how quality scores from the End Stage Renal Disease Quality Incentive Program (ESRD QIP) influences a competitor's entry decision and physician referrals to low quality dialysis centers. Bertuzzi et al. (2023) estimates strategic patient selection for dialysis centers faced with a payment penalty through the ESRD QIP. Eliason et al. (2024) shows that dialysis centers located in different geographic regions administer a dialysis medication at different dosages, highlighting heterogeneity between dialysis treatment centers. I expand on their finding of provider heterogeneity by considering patient preferences, and

outcomes that can be influenced by both the dialysis center and the dialysis patient.

The paper proceeds as follows. Section two explores the role of dialysis and Medicare for patients with end stage renal disease. Section three introduces the data and summary statistics. Section four develops the empirical specification, and section five presents the estimation results. Section six concludes.

### 2.2 Dialysis and the Role of Medicare

The kidneys play an essential role in maintaining a healthy environment for the body. A pair of healthy kidneys will remove toxins in the blood that build up from metabolic processes, remove excess fluid, and secrete hormones to stimulate the production of red blood cells. Patients can progressively lose the function of their kidneys as a result of other diseases, such as diabetes and high blood pressure. As the kidneys lose their ability to function, patients are diagnosed with early stage chronic kidney disease (CKD). Left unchecked, patients can develop kidney failure, also known as end stage renal disease (ESRD) and stage 5 CKD. Patients with ESRD will accumulate a detrimental amount of toxins and fluid, threatening a patient's overall health and mortality.

There are two treatments for kidney failure. First, a patient can receive a kidney transplant from a living or deceased donor. Kidney transplantation is the preferred method to treat ESRD. A successful kidney transplant removes the need for continuous dialysis treatment. However, the supply of viable kidneys is far outpaced by demand (U.S. Renal Data System, 2023). As a result, patients will often spend several years on a kidney transplant waitlist before they are matched to an appropriate kidney or are removed from the waitlist.

The other treatment available for kidney failure is dialysis. A patient undergoing dialysis has three options. By far the most common type is in-center hemodialysis.[1] During dialysis, the patient's blood is passed through a machine several times. The dialysis machine filters out the waste, toxins, and fluid that are normally removed by kidneys. Some medications are added to replace the hormones typically created in the kidneys, and the blood is then returned to the patient. A typical dialysis session lasts about three to four hours, and treatment generally occurs three

[1] In the remainder of the paper, I refer to in-center hemodialysis as dialysis.

times per week for the life of the patient. The second option is home dialysis, which is similar to in-center hemodialysis but relies on a smaller machine in the patient's home. The last option is peritoneal dialysis, where fluid is introduced into the lining of the abdomen. The fluid naturally draws out toxins and is removed after a few hours. Peritoneal and home dialysis can pose additional out-of-pocket costs[2] for patients and a patient must meet certain inclusion criteria.[3]

Since 1972, The Centers for Medicare & Medicaid Services (CMS) has provided full Medicare coverage for patients diagnosed with ESRD. Dialysis services are covered under Medicare Part B, which reimburses outpatient services. When a patient is diagnosed with ESRD, Medicare becomes the primary payer after three months of treatment if a patient is uninsured or has public health insurance, or after 30 months of treatment if a patient has private insurance. In 2012, CMS launched the End Stage Renal Disease Quality Incentive Program, transitioning from a fee-for-service (FFS) reimbursement scheme to a prospective payment system (PPS) with value-based purchasing. Under the old FFS scheme, dialysis centers were reimbursement per treatment but could separately bill for highly reimbursable medications. In the PPS scheme, dialysis centers are reimbursed a fixed, bundled rate for each treatment, which includes a fixed cost for medications.

There are over 7,000 dialysis facilities across the United States. Dialysis markets are dominated by large, for-profit chains, namely Davita and Fresenius Medical Care. These two organizations account for well over 60% of dialysis centers and over 90% of all revenue (Eliason et al., 2020). Mergers and acquisitions have been common since the late 1990s (Wollmann, 2020), and over 200 new dialysis centers have opened each year since 2011 (Kepler et al., 2024). Patient outcomes have considerable variability depending on a dialysis center's profit status. For example, patients at a for-profit center have a 15% higher relative rate of hospitalization compared to patients at non-profit centers (Dalrymple et al., 2014). Dialysis center heterogeneity also accounts for differences in medication dosages (Eliason et al., 2024), which can have immediate effects on patients.

[2]Peritoneal and home dialysis generally require daily treatment. However, CMS covers up to three treatments per week. Patients can have supplemental insurance such as Medicare Advantage or private insurance, but may face uncovered costs associated with treatment.

[3]These criteria include a strong home support system and high medical compliance.

## 2.3 Data and Summary Statistics

I use data from the United States Renal Data System (USRDS) from 2007-2019. The USRDS collects information on patients with end-stage renal disease from the Centers for Medicare & Medicaid Services (CMS). CMS contributes patient-level Medicare claims for all inpatient encounters through Medicare Part A; outpatient, dialysis, physician/supplier, and durable medical equipment (DME) through Medicare Part B; and prescription drug coverage through Medicare Part D. The claims include information for each dialysis session, as well as line-item details for all hospitalizations, surgeries, and physician services. USRDS also collects information on dialysis centers, such as facility characteristics and annual patient outcomes. In separate analyses, I use data from 2012-2019 to include more detailed dialysis information, such as vascular access and blood levels for hemoglobin and hematocrit.

Patients with ESRD are eligible for Medicare coverage starting in third month of treatment if they are uninsured or have public insurance, or the $30th$ month of treatment if they have private insurance. My primary outcome of interest is health utilization, which I define as the amount reimbursed by CMS for a medical service. Not all patients have Medicare as their primary payer, rendering their utilization as incomplete or missing. I omit patients that are not fully covered by Medicare, have Medicare coverage for only part of the year, or are covered by Medicare Advantage. I require that patients are present in the data for at least three years, which avoids right-skewed utilization in the early months of dialysis treatment (League et al., 2022a). This requirement also presents a sufficient amount of time for patients to be treated at their old and new dialysis centers. Last, I omit patients that are at dialysis centers with fewer than 11 patients in a given year for privacy concerns. My sample consists of about 580,000 unique patients and over 3 million patient-years.

I exploit a change in a patient's utilization environment by considering patients that switch to a new dialysis center. The utilization environment is the average utilization for all patients treated at a dialysis center. I consider a patient as a switcher if they change their annual modal dialysis center from center $j$ in year $t$ to center $j'$ in year $t+1$. The patient must remain at center $j'$ for all subsequent years. Patients that switch back to their origin center or those that change to a

new dialysis center a second time are omitted, although the results are robust to including these instances.

I isolate plausibly exogenous switches by further restricting the sample to only include switches that occur within a few years of a dialysis center being acquired; within a few years of a new dialysis center opening near the patient; or if the number of patients served at a dialysis center drops below 25% of the total the year before, which I consider to be a closure. Ideally, these three criteria induce a switch that is unrelated to a patient's underlying health or a health shock, which would threaten the causal interpretation of my estimates. While my results are robust to including all switchers and patients that switch following a move, I do observe pre-trends and estimates closer to zero. Including patients that switch due to a move could be capturing place effects. These results are included in Appendix F.

Summary statistics for my sample are shown in Table 2.1. I divide the sample into patients that switch (switchers) and patients that never switch (stayers). In Panel 2.1a, patient demographics are shown for these two groups. Switchers and stayers are equally likely to be male. There are some racial disparities, with switchers being more likely to be Black and slightly less likely to be Hispanic. Switchers are about 3.5 years younger when they start dialysis and are, on average, about a year younger at any given time. They also spend about 6.2 years on dialysis, whereas stayers spend 5 years on dialysis. In total, there are 16,140 unique switchers, representing about 0.5% of the sample.

In Panel 2.1b, I show health characteristics for switchers and stayers. Overall, switchers are slightly healthier, which is consistent with being younger than stayers. For example, switchers have lower rates of congestive heart failure than stayers, 2.55% compared to 2.68%, and lower rates of diabetes, 33.3% compared to 35.9%. Patients that switch are less likely to have diabetes as the primary cause of ESRD. Switchers do have a mortality rate that is 0.24 percentage points higher than stayers.

Table 2.1 Summary Statistics

(a) Patient Demographics

| | Switchers | Stayers |
|---|---|---|
| Male | 0.557 | 0.555 |
| White | 0.367 | 0.397 |
| Black | 0.414 | 0.384 |
| Asian | 0.032 | 0.036 |
| Hispanic | 0.141 | 0.148 |
| Age of First Service | 55.94 | 58.30 |
| Age | 62.62 | 63.79 |
| Employed | 0.117 | 0.111 |
| Retired | 0.488 | 0.528 |
| Nephrologist | 0.682 | 0.714 |
| Mediciaid | 0.299 | 0.295 |
| Years on Dialysis | 6.233 | 5.045 |
| BMI | 30.073 | 29.960 |
| Patient-Years | 104,256 | 3,038,027 |
| Unique Patients | 16,140 | 579,011 |

(b) Patient Health Characteristics

| | Switchers | Stayers |
|---|---|---|
| **Health Characteristics** | | |
| Previous Heart Attack | 0.009 | 0.010 |
| Pericarditis | 0.003 | 0.002 |
| Alcohol | 0.015 | 0.013 |
| Amputation | 0.023 | 0.024 |
| Heart Disease | 0.130 | 0.132 |
| Cancer | 0.043 | 0.049 |
| Congestive Heart Failure | 0.255 | 0.268 |
| COPD | 0.060 | 0.064 |
| Stroke | 0.078 | 0.080 |
| Diabetic | 0.333 | 0.359 |
| High Blood Pressure | 0.908 | 0.907 |
| Inambulatory | 0.037 | 0.039 |
| Assistance with ADLs | 0.066 | 0.076 |
| Peripheral Vascular Disease | 0.098 | 0.102 |
| Smoker | 0.066 | 0.063 |
| Dies During Study | 0.671 | 0.647 |
| **Primary Cause of ESRD** | | |
| Diabetes | 0.437 | 0.465 |
| High Blood Pressure | 0.294 | 0.299 |
| Other Causes | 0.277 | 0.243 |

Notes: Summary statistics for switchers and stayers for all years. Switchers are those that switch their dialysis provider exactly once, stayers are those that never switch to a different dialysis provider. Panel (a) shows demographics; Panel (b) shows health characteristics. Data are from 2007-2019 and are derived primarily from Medicare claims. COPD is chronic obstructive pulmonary disease; ADL are activities of daily living. Mortality is all-cause mortality.

Next, I show the average utilization for switchers and stayers in Table 2.2. Overall, switchers and stayers have similar rates of utilization. The first block of outcomes are payment variables. All spending includes the sum of non-dialysis outpatient, inpatient, and physician/supplier services. Non-dialysis outpatient spending includes preventative services, diagnostic testing, and emergency room costs. Physician and supplier costs are costs directly associated with visiting a physician. Dialysis outpatient spending are payments made directly to dialysis centers. Switchers spend slightly more in total spending than stayers, $38,885 compared to $38,465. We observe similar trends for the other categories of spending, where switches have slightly higher rates of utilization than stayers: $60 more in non-dialysis outpatient spending; $150 more in inpatient spending; and $210 more in physician and supplier spending.

The second block of outcomes compares hospital related outcomes for switchers and stayers. Switchers and stayers have the same number of hospitalizations in a given year, about 1.48. Switchers have fewer hospitalizations that are due to cardiac-related issues but more hospitalizations that are due to vascular-related issues or an infection. Patients that switch dialysis centers spend about 0.16 fewer days in the hospital. They also spend more days in a Critical Care Unit but fewer days in the Intensive Care Unit.

The third block compares dialysis outcomes from 2012-2019, which are largely under the discretion of the dialysis center. EPO (Epoeitin) is a medication used to stimulate the production of red blood cells and help prevent anemia. EPO is dosed based on body weight. Hematocrit is a measure of red blood cells to total blood volume, and hemoglobin is a protein that carries iron, which is essential to transporting oxygen. KtV measures how much urea is removed from the patient over the course of a dialysis session relative to the blood volume of a patient. Switchers tend to have more Epoeitin administered over the course of their dialysis treatment, although this could be due to switchers having a slightly higher BMI than stayers. The last block is vascular access, or how the dialysis center accesses the blood during a dialysis session.[4] A fistula is the preferred method, which is the fusion of a vein and artery in the arm. A catheter is a flexible rubber tube placed in an artery, and a graft is a tube that fuses a vein and artery. Switchers are less likely to have a fistula compared to stayers but more likely to have graft. Overall, Table 2.2 suggests that switchers and stayers have similar levels of utilization across several measures.

[4]Dialysis patients can change their vascular access during the year, which is a decision made in concert with their nephrologist.

Table 2.2 Utilization Summary Statistics

| | Switchers | Stayers |
|---|---|---|
| **Payment Variables** (2007-2019) | | |
| All Non-Dialysis Spending | $38,885.17 | $38,465.77 |
| Non-Dialysis Outpatient | 4,536.11 | 4,475.47 |
| Inpatient | 22,504.73 | 22,358.99 |
| Physician/Supplier | 11,845.27 | 11,631.77 |
| Dialysis Outpatient | 26,154.54 | 25,579.69 |
| **Hospital Outcomes** (count)(2007-2019) | | |
| Hospitalizations | 1.481 | 1.482 |
| Hospitalizations (Cardiac) | 0.386 | 0.403 |
| Hospitalizations (Vascular) | 0.155 | 0.147 |
| Hospitalizations (Sepsis) | 0.099 | 0.100 |
| Hospitalizations (Infection) | 0.063 | 0.058 |
| Hospital Days | 10.38 | 10.54 |
| CCU Days | 0.958 | 0.889 |
| ICU Days | 2.309 | 2.554 |
| Any Hospitalization in Year | 0.580 | 0.584 |
| **Dialysis Outcomes** (2012-2019) | | |
| EPO Dose (1,000 IUs) | 38.98 | 37.50 |
| Hematocrit | 32.88 | 32.69 |
| Dialysis Sessions | 11.24 | 11.15 |
| Hemoglobin | 11.10 | 11.03 |
| KtV | 2.08 | 2.03 |
| **Vascular Access**(2012-2019) | | |
| Fistula | 0.629 | 0.641 |
| Catheter | 0.186 | 0.226 |
| Graft | 0.226 | 0.200 |

Notes: This table presents utilization summary statistics for switchers and stayers. Data from 2007-2019 are derived from Medicare claims; data from 2012-2019 are derived from dialysis-specific Medicare claims through CROWNWeb. All non-dialysis spending includes inpatient, non-dialysis outpatient, and physician and supplier claims. Non-dialysis outpatient includes office visits, outpatient care, and preventative services. Inpatient claims include hospitalizations and surgeries. Dialysis outpatient claims are Medicare reimbursements to dialysis providers for dialysis services. Hospitalizations are all-cause hospitalizations. CCU and ICU days are the number of days spent in a critical care unit or an intensive care unit. EPO dose is the dosage of epoetin alfa, a medication used to treat anemia and is measured in international units (IUs). Dialysis sessions are the number of dialysis treatments per month. KtV is a measure of dialysis adequacy, which is how much urea is removed from the body as a function of time and a patient's blood volume. Vascular access is the method used to access the blood.

## 2.4 Empirical Specification

I begin my empirical specification by presenting the components of dialysis patient utilization attributable to dialysis center heterogeneity, such as treatment intensities or attention to patient health, and dialysis patient heterogeneity, such as a patient's propensity to seek out health services or their health endowment. This empirical specification follows Finkelstein et al. (2016) Fadlon and Parys (2020), and Godøy and Huitfeldt (2020), where a patient $i$'s health utilization at time $t$ is expressed as a function of patient heterogeneity, dialysis provider heterogeneity, and time-varying patient characteristics:

$$y_{it} = \alpha_i + \delta_{j(i,t)} + \lambda X_{it} + \tau_t + \varepsilon_{ijt} \tag{2.1}$$

Here, $y_{it}$ is the health outcome of interest for patient $i$ at time $t$; $\alpha_i$ is a patient fixed-effect; $\delta_{j(i,t)}$ is the effect dialysis center $j$ on the outcome of patient $i$, where $j(i,t)$ indicates that patient $i$ is being treated at center $j$ at time $t$. $X_{it}$ includes time varying patient characteristics, such as 5-year age bins and a relative year fixed effect $\rho_{r(i,t)}$ for a switcher that changes dialysis centers at time $t^*$, where the relative year is $r(i,t) = t - t^*$. $\tau$ are calendar-year fixed effects.

Equation 2.1 is the baseline specification to estimate the amount of variation in patient utilization that is attributable to their dialysis center. In order to view this effect as causal, patients must experience a plausibly exogenous change in their utilization environment. A patient's decision to switch dialysis centers needs to be uncorrelated with underlying health such that, in the absence of a switch, their utilization progression would not have changed. I exploit a patient's decision to switch to a new dialysis center $j'$ within two years of the acquisition of their current dialysis center $j$, within two years of a new competitor opening a facility near the patient, or the patient's dialysis center closing. While these types of switching are under the control of the patient, they are reasonably induced for reasons other than underlying health or health shocks.

The primary utilization variable is log(non-dialysis spending + 1), which captures all non-dialysis related expenditures.[5] The log transformation is attractive in this setting because of the

[5]Other specifications use the individual inputs of non-dialysis spending (inpatient, outpatient non-dialysis, physi-

skewed nature of total spending. For patient $i$, who is treated at dialysis center $j$ and switches to center $j'$, let $\Delta_i \equiv \bar{y}_{j'} - \bar{y}_j$, where $\bar{y}_j$ is the average outcome of all patients across time.[6] For non-switchers, $\Delta_i$ is normalized to zero. Empirically, $\Delta_i$ acts as a scaling factor that captures both the magnitude and the direction of the change Finkelstein et al. (2016), allowing patients to differ in terms of their origin dialysis center.

We can identify dialysis center effects using a potential outcomes framework (Huang and Ullrich, 2024). Let $y_{it}(1)$ be the utilization after a switch to a new dialysis center $j'$ from $j$, and $y_{it}(0)$ be the utilization prior to a switch. Then the potential outcomes can be expressed as:

$$y_{it}(1) = \alpha_i + \delta_{j'} + \lambda X_{it} + \tau_t + \varepsilon_{it}$$
$$y_{it}(0) = \alpha_i + \delta_j + \lambda X_{it} + \tau_t + \varepsilon_{it}$$

The difference in dialysis center treatment styles, $\delta_{j'} - \delta_j$, is equal to the difference $y_{it}(1) - y_{it}(0)$. I standardize this measure by dividing by the difference in average utilization $\Delta_i$. As shown in Finkelstein et al. (2016), the difference across all origin dialysis centers $j$ and destination dialysis centers $j'$ that is attributable to a dialysis center's utilization environment is then $\beta \equiv \frac{\delta_{j'} - \delta_j}{\bar{y}_{j'} - \bar{y}_j}$. Using $r(i,t) = t - t^*$ as time relative to a patient's switch and $\mathbf{I}_{r(i,t)>0}$ as an indicator for relative time periods greater than zero, then for switching patients we can write:

$$y_{it} = \alpha_i + \delta_j + \beta \Delta_i \mathbf{I}_{r(i,t)>0} + \lambda X_{it} + \tau_t + \varepsilon_{it} \tag{2.2}$$

The $\beta$ is the parameter of interest: it represents the average change in health utilization in the years following a switch, relative to the overall difference in utilization environment between the destination and origin dialysis centers. In other words, $\beta$ is the change in a patient's own utilization when they switch to a dialysis center with average utilization one unit higher. If all the change in a patient's utilization is due to patient effects, then $\beta$ would be equal to zero: utilization after a switch

cian/supplier), as well as all hospitalizations; hospitalizations that are cardiac in nature or vascular-related; and two variables related to dialysis-specific measures: use of a fistula for dialysis access, and KtV, which is a measure of dialysis adequacy.

[6]The estimates are robust to excluding the year a patient switches, but the estimates are less precise.

does not depend on the change in utilization at the dialysis center. Conversely, if all the change is due to the new dialysis center, then $\beta$ will approach one. It is important to note that $\beta$ does not give any indication of how much of a patient's *total* spending is due to their dialysis center, but rather how much of the *variation* in total spending is due to the differences between their origin and destination dialysis centers.

One assumption that I use to help estimate Equation 2.2 is that a patient's decision to switch is not perfectly correlated with a shock to their own health (Finkelstein et al., 2016; Godøy and Huitfeldt, 2020). If this were the case, then the estimate of $\beta$ would be biased depending on the shock. For example, if a patient is diagnosed with a disease that requires frequent treatments at a hospital, and the patient decides to switch to an nearby dialysis center that treats other high-utilization patients, then $\beta$ would be biased upward. A few features of the data suggest that this is not the case. First, switchers and stayers have similar levels of utilization, so those that switch are not systematically different along the outcomes of interest. Second, I show in the next section that the coefficients leading up to the time of a switch are not statistically different from zero. The lack of pre-trends suggests that patient health is not trending upward or downward relative to the time they switch, and the lack of a jump immediately prior to a switch suggests that there are no health shocks that precede a switch.

I take two equations to the data. First, rewriting $\tilde{\alpha}_i = \alpha_i + \delta_j$, and letting $Post_{it} = 1$ for the time periods after a switch and $Post_{it} = 0$ for the time periods prior to a switch, we can express Equation 2.2 as

$$y_{it} = \tilde{\alpha}_{it} + \beta Post_{it}\Delta_i + \lambda X_{it} + \tau_t + \varepsilon_{it} \tag{2.3}$$

Since switchers are restricted to at most one switch, $\Delta_i$ is absorbed in the patient fixed-effect. Additionally, switchers remain in the same geographic area. As a result, any place effect from their geographic region is differenced through the patient fixed-effect. Equation 2.3 represents a standard difference-in-differences estimation.

Second, I allow for the utilization environment to dynamically affect a patient's own utilization

by interacting $\Delta_i$ with relative time indicators:

$$y_{it} = \tilde{\alpha}_i + \sum_{r \neq -1, r=-6}^{r=6} (\beta_r \text{ x } \Delta_i \text{ x } \mathbf{I}_r) + \lambda X_{it} + \tau_t + \varepsilon_{it} \tag{2.4}$$

where $\mathbf{I}$ = 1 when $r(i,t) = r$ represents binary time indicators for year $r$ relative to the switch. The reference year is the year prior to a switch, or the last year a patient is at their original dialysis center. I normalize all interaction terms to zero for non-switchers. The event study specification is used to test for parallel-trends, $\beta_r = 0, r < -1$, as well as to investigate the dynamic effects after a switch for $r >= 0$. Equations 2.3 and 2.4 are estimated with robust standard errors clustered at the patient's current dialysis center.

The identifying assumption is that patients exposed to a different utilization environment $\Delta_i$ following a switch to a new dialysis center would have had utilization that ran parallel in the absence of a switch. A patient's own utilization must therefore not vary systematically depending on $\Delta_i$. This assumption would fail, for example, if patients that experience a shock to their own healthcare costs are more likely to switch if they are at a low utilization center instead of a high utilization center. The restrictions I use to identify switches are likely exogenous and help alleviate some of this concern since a switch must coincide with a new entrant, an acquisition, or a closure. However, some patients could still be selecting into high or low utilization environments. In the next section, I show the distribution of $\Delta_i$ and provide some evidence that patients are not systematically sorting based on origin dialysis center utilization.

## 2.5 Results

I now present my results, beginning with an exploration of the utilization environment. I then show the point estimates and event study representation from estimating Equations 2.3 and 2.4.

### 2.5.1 Utilization Change Distribution

Table 2.3 shows the mean, standard deviation, $25^{th}$ and $75^{th}$ percentiles for the log and level values for various $\Delta_i$ measures. The first four rows are the log values of total spending, inpatient, non-dialysis outpatient, and physician/supplier spending. The levels of these four variables are

shown in the next five rows. Rows 10-15 show other outcomes of interest, namely all hospitalizations, hospitalizations due to vascular complications and cardiac complications, KtV, and whether the patient has a fistula for vascular access.

Table 2.3 $\Delta_i$ Values for Switchers

| $\Delta_i = \bar{y}_{j'} - \bar{y}_j$ | Mean | SD | 25th Percentile | 75th Percentile |
|---|---|---|---|---|
| Log(Total Spending) | 0.039 | 0.258 | -0.096 | 0.174 |
| Log(Inpatient) | 0.038 | 0.399 | -0.142 | 0.210 |
| Log(Outpatient) | 0.079 | 0.381 | -0.111 | 0.280 |
| Log(Physician/Supplier) | 0.023 | 0.290 | -0.114 | 0.168 |
| Total Spending | $1442.60 | $ 9245.60 | -$3618.86 | $6609.07 |
| Inpatient | $783.01 | $6694.80 | -$3138.38 | $4609.23 |
| Outpatient | $378.61 | $1469.21 | -$444.52 | $1190.72 |
| Physician/Suppler | $280.97 | $3696.23 | -$1279.85 | $1706.29 |
| Hospitalizations | -0.018 | 0.427 | -0.259 | 0.226 |
| Vascular Hospitalizations | -0.020 | 0.100 | -0.066 | 0.028 |
| Cardiac Hospitalizations | -0.006 | 0.152 | -0.088 | 0.081 |
| KtV | -0.091 | 0.596 | -0.277 | 0.118 |
| Fistula | 0.006 | 0.120 | -0.060 | 0.073 |
| Observations | 104,252 | | | |

Notes: This table shows the mean, standard deviation, 25th and 75th percentiles for various $\Delta_i$ values. The sample includes all switch-years, $N = 104,252$. Stayers have $\Delta_i$ values normalized to 0 and are therefore omitted from this table.

A positive value for $\Delta_i$ indicates that patients are switching to a higher utilization dialysis center relative to their origin center. Table 2.3 shows that the log-values are close to zero, whereas the level values have more variation and are shifted to the right. This is primarily due to dialysis patients having high utilization levels to begin with, which motives the use of the log transformation. The other outcomes of interest, in rows 10-15, have a slightly negative mean value, suggesting that dialysis patients switch to a new dialysis center with lower rates of hospitalizations and slightly worse KtV, although patients at the new dialysis center are slightly more likely to have a fistula for vascular access, relative to those at the origin dialysis center.

I complement Table 2.3 by plotting the distribution of $\Delta_i$ for all switchers in Figure 2.1,

defining $\Delta_i$ as the difference in average log total non-dialysis spending.[7] Figure 2.1 shows that difference in log-utilization is symmetric around 0 with a mean of 0.039 and standard deviation of 0.258. Figure 2.1 provides evidence that sorting is not much of a concern. If sorting were present, then the distribution would be notably shifted to the right if patients are more likely to switch to relatively higher utilization dialysis centers, $\bar{y}_{j'} > \bar{y}_j$, or to the left if the were more likely to switch to relatively lower utilization centers, $\bar{y}_{j'} < \bar{y}_j$. The distribution in my setting is similar to that of Finkelstein et al. (2016); Godøy and Huitfeldt (2020) and Fadlon and Parys (2020).

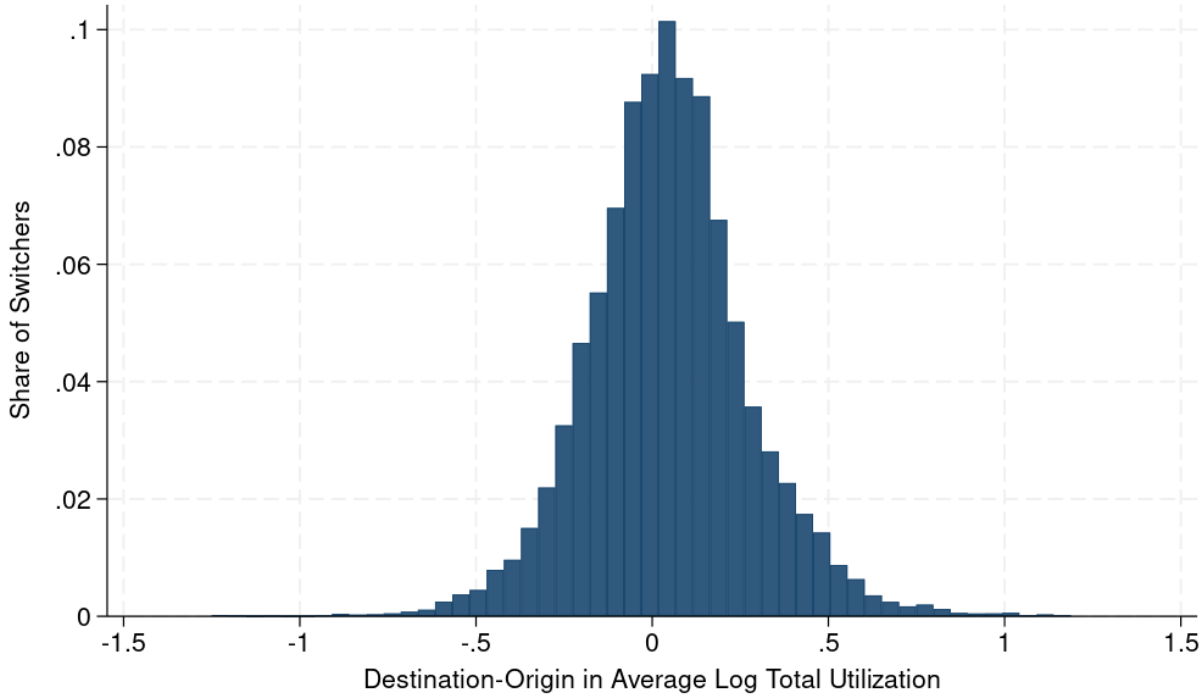



Figure 2.1 Probability of Switching in Each Year

Notes: This figure shows the distribution of $\Delta_i = log(\bar{y}_{j'}) - log(\bar{y}_j)$ for dialysis patients that switch from center $j$ to center $j'$. The difference in logs is symmetric around zero. Distribution is shown for values between -1.5 and 1.5 due to a few outliers. The sample is all patient switch-years, $N = 104,256$

I show early graphical evidence of provider effects in Figure 2.2. In this figure, I graph the relationship between a patient's own change in utilization to the change in their utilization environment, both of which are defined as the log-total of non-dialysis spending. I construct this

[7]The $\Delta_i$ for other outcomes is similarly distributed, as shown in Table 2.3.

graph by first calculating the difference between a patient's average utilization 2-5 years after a switch and 2-5 years before a switch.[8] Then, for each $\Delta_i$ ventile, I find the average change in patient utilization. If all variation in spending is due to provider effects, then we would expect a slope equal to one. If patient effects dominate, then the slope should be closer to zero (Finkelstein et al., 2016). Figure 2.2 shows that the relationship has a slope of 0.524, indicating that roughly 52% of variation in total spending is due to dialysis center heterogeneity.

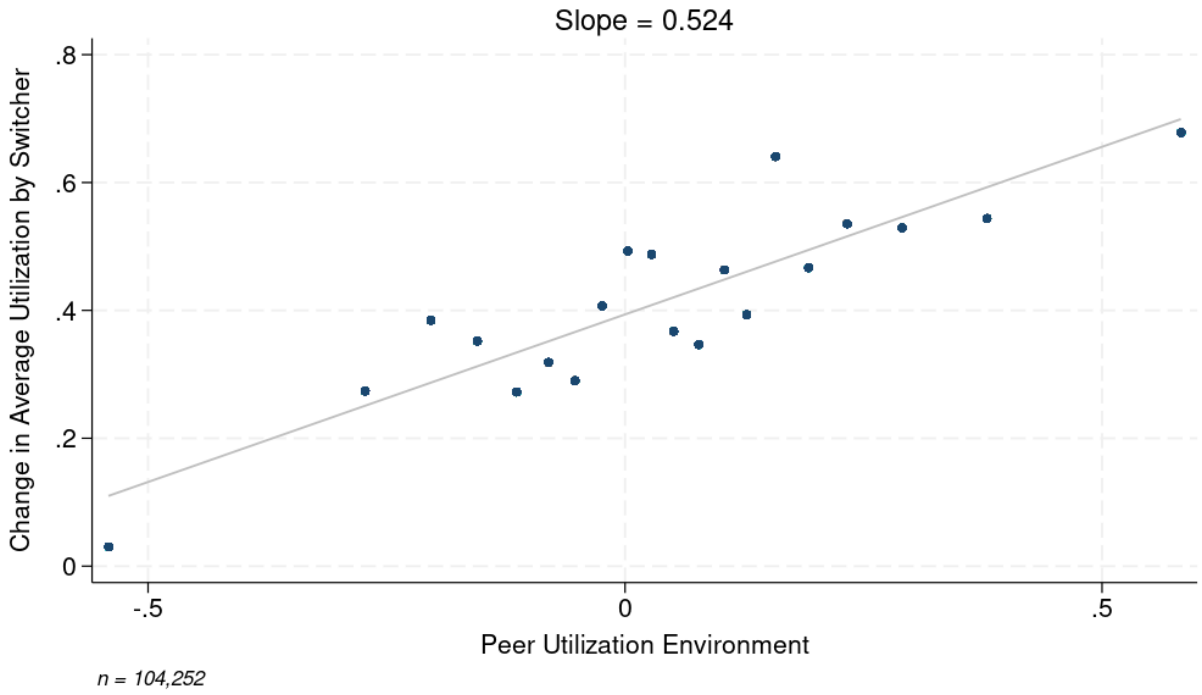



Figure 2.2 Change in Log-Utilization After Switch

Notes: This figure plots the 2-5 year difference in log utilization against ventiles of $\Delta_i$. For each patient that switches, I calculate the average utilization 2-5 years prior to a switch and 2-5 years after a switch. If a patient is not in the data for 5 years prior or 5 years after a switch, I use the years that are available. I then take the difference in logs. For all $\Delta_i$ values, I separate into 20 ventiles and find the average log change in utilization. The line of best fit is obtained from a simple OLS regression using the 20 ventiles of $\Delta_i$ and the change in log utilization. The sample includes all switch-years $N = 104,256$. Non-switchers are omitted.

Next, I divide the sample into four categories: utilization at the origin dialysis center that is below or above the average, and $\Delta_i$ that is above or below 0. Let $\Delta_{>0} = 1$ if $\Delta_i$ is positive and 0 otherwise, and $Higher_{it} = 1$ if a patient's average utilization at their origin dialysis center is greater

[8] This can be considered an analogous $\Delta_i$ for each patient.

than the origin dialysis center's average, and 0 otherwise. I define $\tilde{y}_{ijt}$ as demeaned log-utilization, where I subtract the log-average utilization at dialysis center $j$ at time $t$ from the log-utilization of patient $i$ at dialysis center $j$ at time $t$. Note that after a switch, $\tilde{y}_{ijt}$ subtracts the new dialysis center's log-average utilization. I then estimate via OLS:

$$\tilde{y}_{ijt} = \sum_{r=-10}^{r=10} (\beta_r * \Delta_{>0} * Higher_{it}) + \lambda * X_{it} + \tau_t + \varepsilon_{it} \tag{2.5}$$

where $X_{it}$ includes 5-year age brackets and whether a patient is hospitalized in a given year, and $\tau$ are calendar year fixed-effects. The predicted values are plotted in Figure 2.3. Although not causal, the figure gives an indication for how a dialysis patient's utilization progresses relative to the average of their current dialysis center.

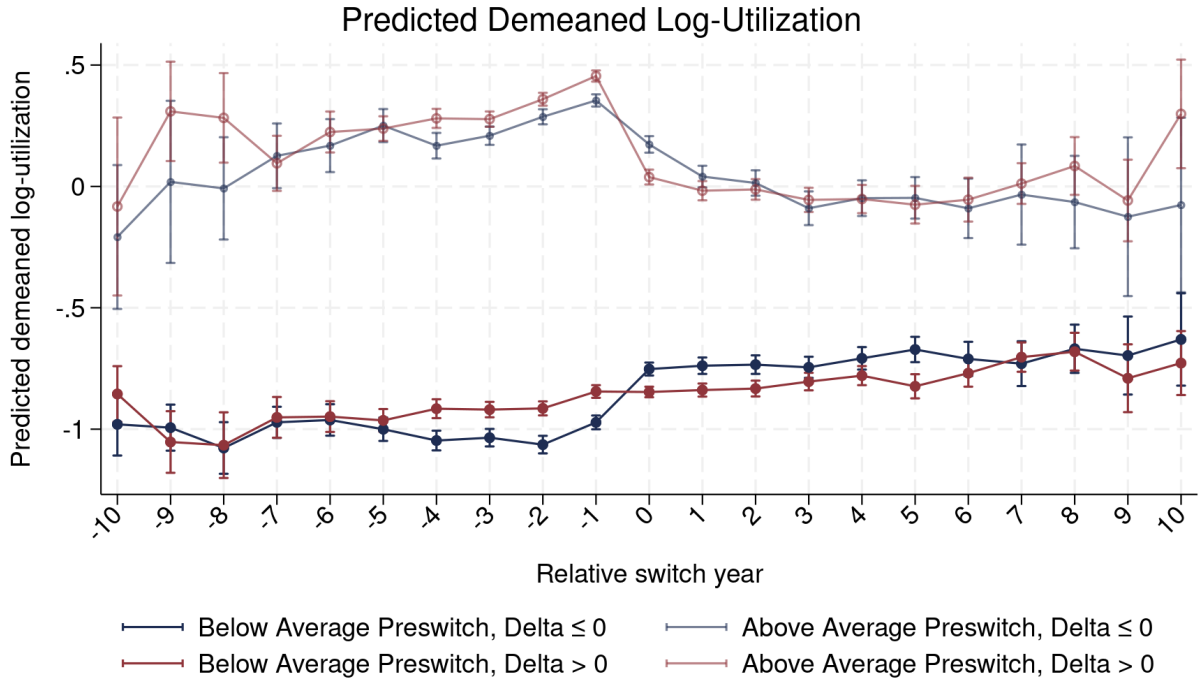



Figure 2.3 Demeaned Utilization by Average Spending a $\Delta_i$

Notes: This figure shows the predicted demeaned log-utilization for four categories of switchers: $\Delta_i \leq 0$ and $\Delta_i > 0$, and pre-switch utilization less than or equal to the origin dialysis center's log-average or greater than the origin dialysis center's log-average. Solid lines at the bottom are patients with below average pre-switch spending and negative (blue) and positive (red) $\Delta_i$. The top two lines are patients with above average pre-switch spending and negative (blue) and positive (red) $\Delta_i$. Estimation includes 5-year age category, a binary variable for whether a patient is hospitalized, and calendar-year fixed-effects. Standard errors are clustered at the dialysis provider level.

There are a few notable features. First, there is clear separation between patients with below or above average pre-switch spending. The solid red and blue lines in the bottom half of the figure are patients with below average spending. The two lines in the top half are patients with above average spending. Second, the $\Delta_i$ influences the trajectory of a patient's spending. For patients with below average spending, demeaned utilization is slightly higher for patients that switch to a relatively higher spending dialysis center. After the switch, the trend inverts, where patients at relatively lower spending dialysis centers have a larger increase in their demeaned spending. For patients with above average spending, a positive $\Delta_i$ is associated with slightly higher demeaned spending prior to a switch, but the values converge in the years following a switch. Interestingly, patients with above average spending see a spike in their spending in the year immediately prior to their switch. This feature is not present for patients with below average spending. Additionally, patients with above average spending have demeaned utilization that converges to the average of their new dialysis center. Patients with below average spending do shift their spending closer to the new dialysis center's average, but it remains well below the average in years following a switch.

Figure 2.3 shows that the progression of utilization does depend on the value of $\Delta_i$. However, this does not indicate that patients are sorting based on $\Delta_i$. If sorting were present, this figure would show a similar trend for patients with a positive (or negative) $\Delta_i$. For example, we might observe that all patients with a positive $\Delta_i$ increase their spending after a switch and vice-versa for patients with a negative $\Delta_i$. My model permits patients to vary arbitrarily based on their pre-switch utilization by explicitly controlling for the patient fixed-effect. Additionally, patients can vary arbitrarily based on their respective $\Delta_i$ via the interaction term.

I last show how total spending progresses for switchers, based on their origin and destination dialysis center's average spending in Figure 2.4. For all switchers, I separately group the origin and destination dialysis centers into quartiles of (log) total spending. I then plot how a patient's (log) total spending progresses for those that switch from one quartile into another, in the same spirit of Card et al. (2013). For clarity, I include patients that originate at either the lowest or highest average spending dialysis centers, i.e. quartiles one and four, and show the average spending for

those that switch to all four quartiles.

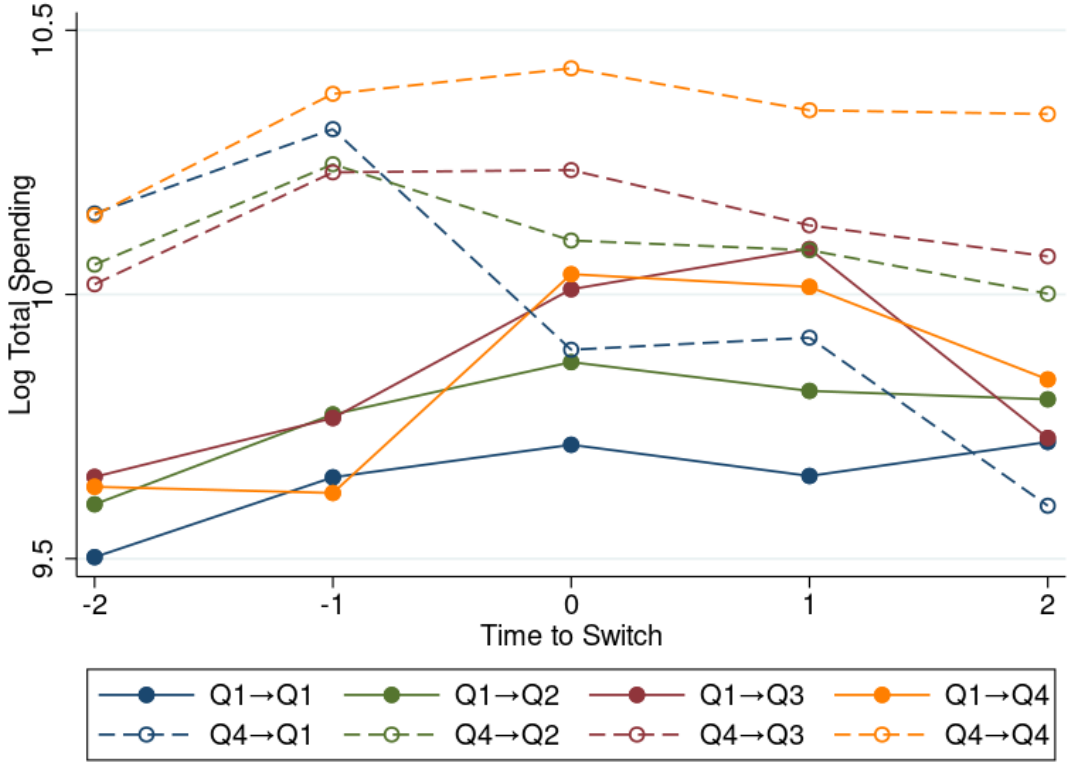



Figure 2.4 Average Log-Total Spending for Switchers by Origin and Destination Spending Quartile
Notes: This figure shows the progression of log total spending for patients that originate at dialysis centers with the lowest and highest quartiles of average spending. Patients are further divided into four quartiles of average spending at their destination dialysis center.

The bottom four solid lines represent patients that originate at dialysis centers in the lowest quartile of average log-total spending. The top four dashed lines are patients that originate at dialysis centers in the highest quartile of average log-total spending. There are a few features of interest in this figure. First, Figure 2.4 suggests that both patient effects and provider effects influence a patient's utilization. If only patient effects were present, then the change in utilization would be unrelated to the origin and destination dialysis provider, and we would observe a relatively flat line for all patients. If only provider effects were present, then the change in utilization would be symmetrical for patients switching to the opposite type of dialysis provider. For example, the change in utilization for patients switching from Q1→Q4 would be equal in magnitude but of the opposite sign to those who switch the other direction.

Second, there is clear separation between patients that originate at the bottom or top quartiles of average dialysis center utilization. Patients at the lowest quartile have lower (log) total spending than those at the highest quartile, even after conditioning on the average spending of the destination dialysis center. This suggests that, within an origin dialysis center, patients are not sorting to their new dialysis center based on their own spending. That is, patients that go to a low utilization destination and those that go to a high utilization destination have similar levels of spending before a switch. Last, patients switching to a similar spending dialysis center, e.g. Q1→Q1, have minimal changes to their own spending, and those that switch to dialysis centers that are most dissimilar, e.g. Q1→Q4, have the largest change in their own spending, even after conditioning on the origin center's average utilization. Additionally, the symmetry of Figure 2.4 suggests that patient- and provider-effects may be characterized as additively separable (Card et al., 2013), which is an attractive feature when using healthcare spending (Finkelstein et al., 2016).

### 2.5.2 Difference-in-Difference

I now show the difference-in-difference estimates from Equation 2.3. The interaction of the $\Delta_i$ and $Post$ is the variable of interest: the coefficient shows how a dialysis patient's utilization changes following a switch to a new dialysis provider, relative to their spending at the origin dialysis center. I include 5-year age brackets as the time-varying control variable. The individual $\Delta_i$ term is absorbed into the patient fixed-effect. Additionally, any place effects are differenced out of the coefficient because patients remain in the same location (Fadlon and Parys, 2020).

The first estimates are shown in Table 2.4. In this table, I do not include any indicators for a patient's health. The top panel uses the log-transformed utilization variable and difference in logs for $\Delta_i$; the bottom panel uses the level values. The effect on total spending is 0.612, indicating that a dialysis patient that switches to a provider with utilization 1 percent higher increases their own spending by 0.612 percent. The magnitude is slightly lower for physician and supplier spending, and above unity for inpatient spending and about 0.90 for outpatient spending. In the second panel, the coefficient associated with total spending is 0.527, which is slightly lower than the log transformed coefficient. In terms of magnitude, this indicates that a patient switching to a dialysis

center with average total spending one standard deviation higher will increase their total spending by about $4,800 ($9,245 * 0.527). A patient that switches to a dialysis center with non-dialysis spending one standard deviation higher experiences an increase in their own non-dialysis outpatient spending of about $925 ($1,469*0.635).

Dialysis patients are high risk and have high medical expenditures, relative to non-ESRD patients. It could be the case that not controlling for health status gives biased results. To see if this is the case, I repeat the same estimation but include a binary indicator variable for whether a patient is hospitalized in a given year. These results are shown in Table 2.5.

Table 2.4 Primary Estimation without Health Indicators

| | (1) Total Spending | (2) Physician/Supplier | (3) Inpatient | (4) Outpatient |
|---|---|---|---|---|
| $\Delta_i$*$Post$ (Log) | 0.612*** | 0.573*** | 1.148*** | 0.903*** |
| | (0.052) | (0.046) | (0.090) | (0.050) |
| $\Delta_i$*$Post$ (Level) | 0.527*** | 0.581*** | 0.580*** | 0.635*** |
| | (0.033) | (0.044) | (0.035) | (0.027) |
| Top panel R-squared | 0.456 | 0.559 | 0.348 | 0.388 |
| Standard errors are clustered at the dialysis center level<br>*** p<0.01, ** p<0.05, * p<0.1 | | | | |

Notes: This table shows the results from estimating equation 2.3. The outcome of interest is either the log-utilization (top panel) or level utilization (bottom panel) for total spending in Column 1; physician/supplier spending in Column 2; inpatient spending in Column 3; and non-dialysis outpatient spending in Column 4. The sample includes all switch-years. *N = 102,282*

Overall, the estimates are more reasonable for both the log values (top panel) and level values (bottom panel). For example, the effect on total spending is reduced to 0.376 for the log value and 0.390 for the level value, which are about 25 base points and 14 base points lower than the estimation without the hospitalization indicator, respectively. The biggest change is in inpatient spending, with a reduction of nearly 100 base points and 18 base points, respectively, for the log and level terms. This is to be expected, since hospitalizations account for most inpatient spending. Controlling for the binary hospitalization variable does not change the estimates for physician/supplier spending

or non-dialysis outpatient spending. Again, this is to be expected, as hospitalizations are billed through inpatient spending. For categories where we would expect a dialysis center to have much less influence (inpatient spending), there is a much smaller effect. The effect is larger when a dialysis center could reasonably influence whether a patient seeks out services, such as outpatient and physician spending. In Appendix G, I repeat the same estimation for different subgroups of patients to show how the response changes based on observable patient characteristics, such as age, race, and urbanicity. I use total non-dialysis spending as the outcome of interest. The results are shown in Table B.1.

Table 2.5 Primary Estimation with Hospitalizations

| | (1) Total Spending | (2) Physician/Supplier | (3) Inpatient | (4) Outpatient |
|---|---|---|---|---|
| $\Delta_i$*$Post$ (Log) | 0.376*** | 0.528*** | 0.189*** | 0.894*** |
| | (0.048) | (0.046) | (0.029) | (0.049) |
| $\Delta_i$*$Post$ (Level) | 0.390*** | 0.558*** | 0.411*** | 0.632*** |
| | (0.029) | (0.042) | (0.031) | (0.027) |
| Top panel R-squared | 0.668 | 0.559 | 0.945 | 0.405 |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results from estimating equation 2.3 while controlling for whether a patient is hospitalized in a given year. The outcome of interest is either the log-utilization (top panel) or level utilization (bottom panel) for total spending in Column 1; physician/supplier spending in Column 2; inpatient spending in Column 3; and non-dialysis outpatient spending in Column 4. The sample includes all switch-years. $N = 102,282$.

I repeat the same estimation and use non-spending utilization as the outcome of interest. Specifically, I consider all-cause hospitalizations, hospitalizations due to cardiac or vascular complications, KtV, and the presence of a fistula. I include time fixed-effects as well as 5-year age categories. These results are shown in Table 2.6. Column one uses all-cause hospitalizations, Column two considers hospitalizations due to a vascular access complication, and Column three uses cardiac-related hospitalizations as the outcome of interest. Column four considers the change in a patient's dialysis adequacy, as measured by their KtV, and column five estimates the effect on

whether a patient uses a fistula for vascular access.

Table 2.6 Other Health Outcomes

| | (1) All-Cause Hospitalizations | (2) Vascular Access Hospitalizations | (3) Cardiac Related Hospitalizations | (4) KtV | (5) Fistula |
|---|---|---|---|---|---|
| $\Delta_i * Post$ | $0.511^{***}$ | $0.712^{***}$ | $0.626^{***}$ | $0.919^{***}$ | $0.322^{***}$ |
| | (0.032) | (0.033) | (0.039) | (0.039) | (0.031) |
| Observations | 166,437 | 166,437 | 166,437 | 77,716 | 78,303 |
| R-squared | 0.483 | 0.298 | 0.372 | 0.449 | 0.815 |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results from estimating equation 2.3 using other health outcomes as the dependent variable. The outcomes include all-cause hospitalizations in Column 1; vascular access related hospitalizations in Column 2; cardiac related hospitalizations in Column 3; and KtV, which is a measure of dialysis adequacy, in Column 4, and whether a patient has a fistula for dialysis access in Column 5. The sample includes all switch-years. Columns 1-3 use data from 2007-2019; Columns 4 and 5 only include data starting from 2012-2019.

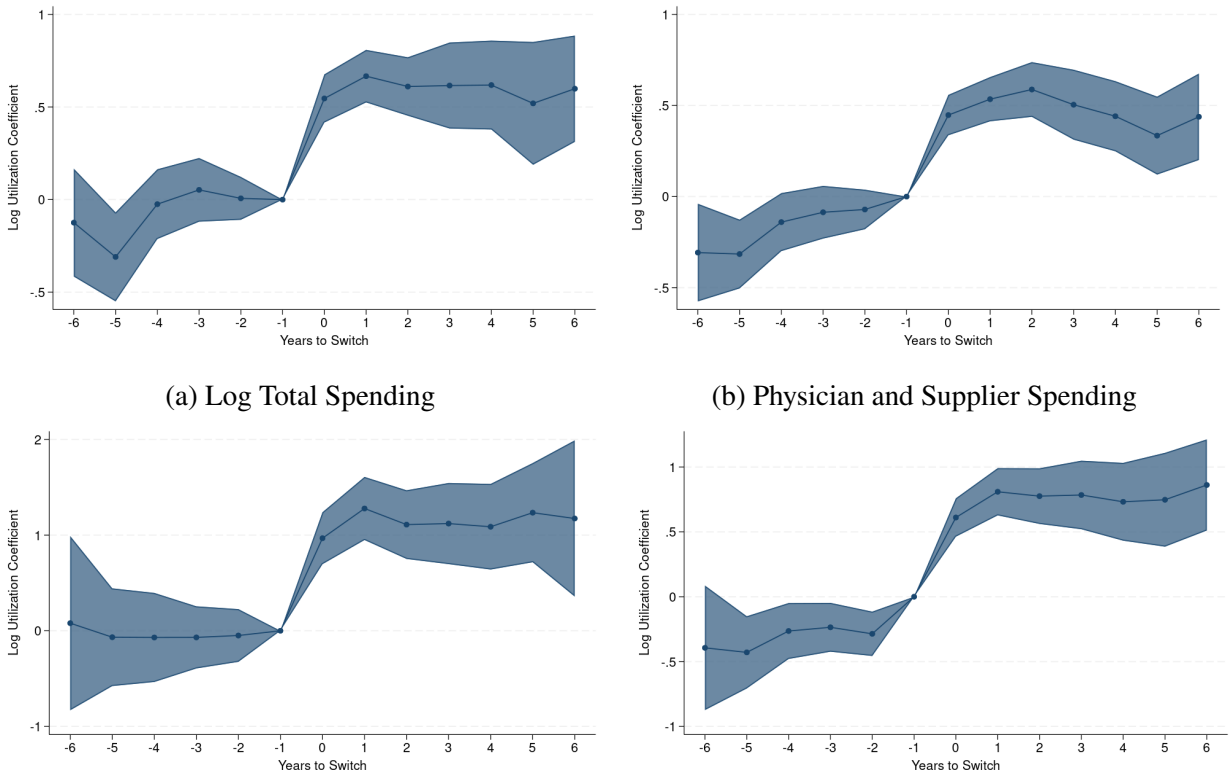
We should expect dialysis centers to influence outcomes that are more within their scope (Fadlon and Parys, 2020). For example, dialysis centers should have more influence on whether a patient has a hospitalization due to vascular complication because of the near daily use of a patient's fistula, catheter, or graft, and the importance of proper sanitation to prevent access-related infections (Patel et al., 2013). Conversely, patient factors should have more of an influence for all-cause hospitalizations, such as medication compliance. Table 2.5 shows that this is indeed the case. Differences in dialysis centers accounts for about 51.1% of the variation in all-cause hospitalizations, 71.2% of the variation in vascular related hospitalizations, and about 62.5% of the variation in cardiac related hospitalizations. Vascular related hospitalizations include complications due to an infection of the access point for dialysis. Dialysis centers can lower the risk of infection through proper sanitation (Patel et al., 2013; Eliason, 2019). Dialysis centers also have a lot of discretion to influence dialysis adequacy by adjusting a patient's time on dialysis. The estimations affirm this discretion: dialysis centers account for 91.9% of the variation in KtV. Vascular access is less under the control of the dialysis center, however. While having a fistula is the preferred

method of access, the decision is jointly made between a patient and their nephrologist, who takes into consideration a patient's risk factors and preferences. Dialysis centers account for only 32.3% of the variation in access via a fistula.

### 2.5.3 Event Study

Next, I show the results from the event study specification by estimating Equation 2.4. The event study offers two key advantages. First, the estimates can reveal whether a patient experiences shocks to their own utilization prior to a switch by testing whether $\beta_{r<-1} = 0$ for the time-periods prior to a switch. Second, the effects can be tracked in the years following a switch. The coefficients $\beta_{r>=0}$ show whether the effects dissipate over time or remain constant.

Figure 2.5 plots the event study coefficients for the log values of total spending, inpatient spending, outpatient spending, and physician and supplier spending. The $\Delta_i$ variable used corresponds to the same individual outcome variable. Panel 2.5a shows how the log of total spending changes around the time of a switch, conditional on the change in the utilization environment. The coefficient in year $r = -5$ is statistically significant, but otherwise pre-trends are not prevalent. The lack of pre-trends suggests that dialysis patients are not changing their own utilization prior to their switch, conditional on their utilization environment, which supports the identifying assumption discussed earlier. Going from year $r = -1$ to $r = 0$, the last year at the origin dialysis center and the first year at the new dialysis center, patients experience an immediate jump in spending, which is sustained for at least six years following the switch. Physician and supplier spending in Figure 2.5b is similar to total spending, with relatively level spending prior to a switch, and a sustained increase when a patient changes their dialysis center. Both estimates suggest that dialysis centers account for over 50% of the variation in spending when a patient switches. Inpatient spending in Figure 2.5c shows very flat pre-trends prior to a switch. However, the estimates after are above unity, suggesting that dialysis centers account for more than 100% of the variation. The estimates for inpatient spending motivate controlling for whether a patient is hospitalized in a given year. Non-dialysis outpatient spending shows a small pre-trend prior to a switch, but a sustained and level jump after a switch.




(a) Log Total Spending

(b) Physician and Supplier Spending

(c) Inpatient Spending

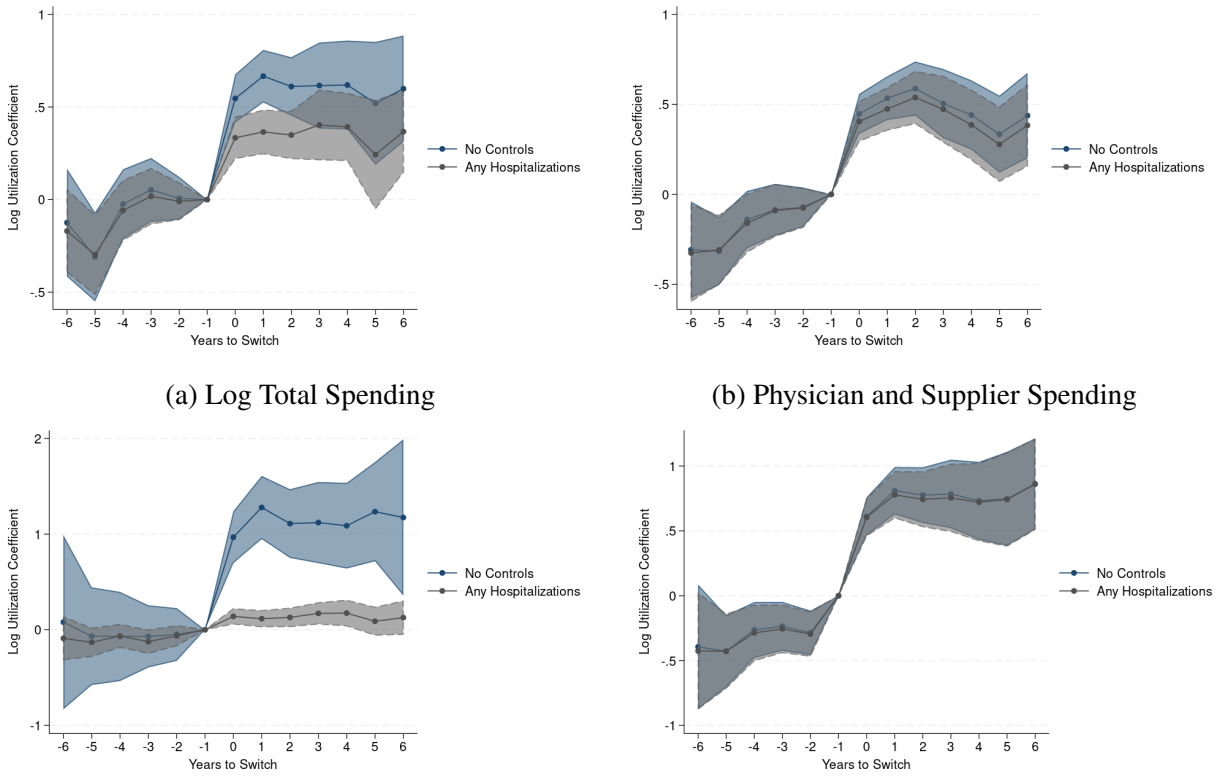
(d) Outpatient Spending

Figure 2.5 Event Study Estimates without Hospitalizations

Notes: Event study estimations from equation 2.4. The year prior to a switch is normalized to zero. Estimates include 5-year age bins as a time-varying control. The top left panel uses the log of total spending; the top right panel uses the log of physician and supplier spending; the bottom left panel uses the log of inpatient spending; and the bottom right uses the log of non-dialysis outpatient spending. Standard errors are clustered at the dialysis center level.

To show the bias that results when not including indicators of health, I repeat the event study specification with the binary hospitalization variable. Figure 2.6 shows the effects from this estimation. The light blue plots are the original estimates without the hospitalization indicator. The gray plots include the hospital variable. The results are notably different for total spending and inpatient spending. There is an approximately 25 base point decrease in total spending when controlling for hospitalizations, and nearly a 100 base point drop in inpatient spending. This is to be expected: hospitalizations account for the vast majority of inpatient spending, which in turn accounts for about half of all non-dialysis spending. The physician/supplier and outpatient spending results do not show much change. These results are consistent with the static difference-

in-difference estimate from Table 2.4, without controlling for hospitalizations, and Table 2.5, which does control for hospitalizations: in categories where we would expect a lot of discretion, dialysis centers have a larger influence on spending.




(a) Log Total Spending

(b) Physician and Supplier Spending

(c) Inpatient Spending

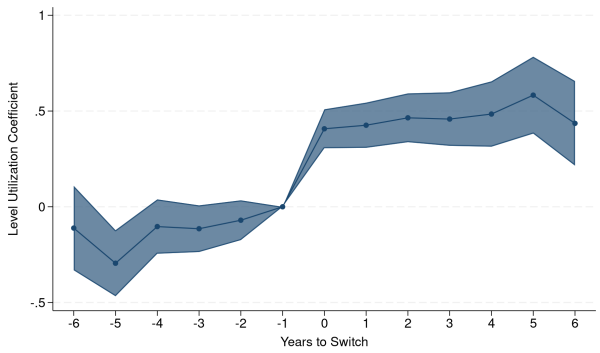
(d) Outpatient Spending

Figure 2.6 Event Study Estimates with and without Hospitalizations

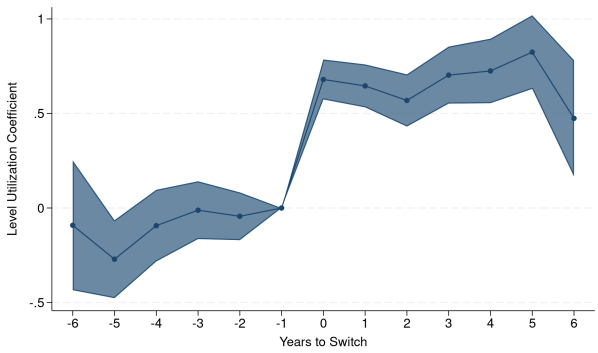
Notes: Event study estimations from equation 2.4. The year prior to a switch is normalized to zero. Estimates include 5-year age bins as a time-varying control. The top left panel uses the log of total spending; the top right panel uses the log of physician and supplier spending; the bottom left panel uses the log of inpatient spending; and the bottom right uses the log of non-dialysis outpatient spending. Standard errors are clustered at the dialysis center level.

Next, I repeat the estimation using the non-spending outcome variables from Table 2.6. Figure 2.7 plots these event study coefficients. The $\Delta_i$ variable used is the same as the outcome variable. The year prior to a switch is normalized to zero and used as a reference year. The top left panel shows the effect on all-cause hospitalizations. The top right panel are hospitalizations due to vascular access related complication. The middle left panel are hospitalizations due to a cardiac complication. The middle right and bottom panels are dialysis adequacy as measured by KtV and

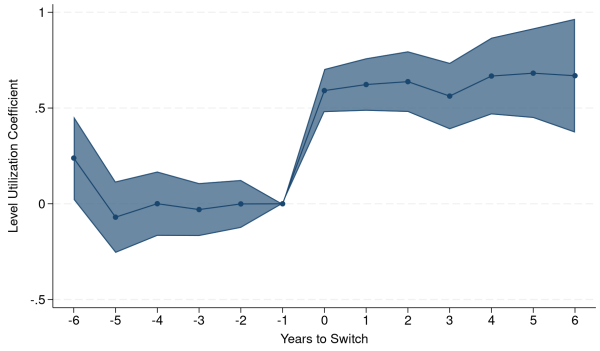
whether a patient has a fistula for vascular access, respectively. All estimations control for 5-year age bins and calendar year fixed-effects. Standard errors are clustered at the dialysis center level.



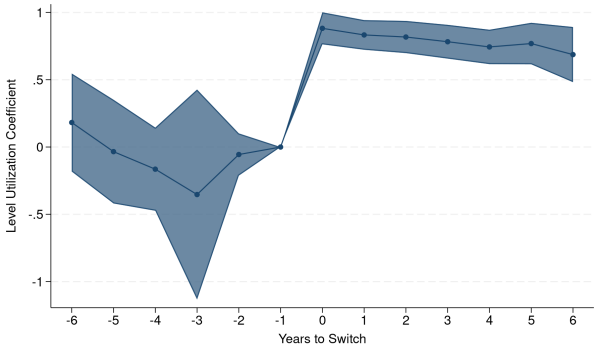

(a) All-Cause Hospitalizations



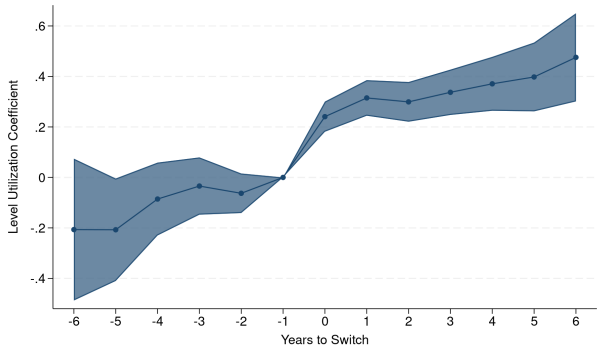

(b) Vascular Related Hospitalizations




(c) Cardiac Related Hospitalizations




(d) Dialysis KtV




(e) Fistula Dialysis Access

Figure 2.7 Event Study Estimates for Other Health Outcomes

Notes: Event study estimations from equation 2.4. The year prior to a switch is normalized to zero. Estimates include 5-year age bins as a time-varying control. The top left panel uses all-cause hospitalizations; the top right panel uses vascular related hospitalizations; and the middle left panel uses cardiac related hospitalizations. The middle right and bottom panels use a patient's KtV and whether they have a fistula for dialysis access, respectively. Standard errors are clustered at the dialysis center level.

All five outcomes exhibit no pre-trends, suggesting that patients are not responding to shocks to their health by switching to a new provider. For example, patients are not choosing to switch because of increasing hospitalization rates. If this were the case, then we would observe a spike in the coefficient in year $t-2$ in the top left panel. We also observe an immediate jump following a switch, suggesting that dialysis centers are immediately influencing the outcomes. Finally, the steady coefficients suggest that the effect is sustained and patients are not reverting to their pre-switch levels. We observe higher estimates for categories where a dialysis center likely has the most influence, suggesting that the estimation is accurately capturing dialysis center heterogeneity. For example, a patient's KtV approaches unity following a switch, which is to be expected because dialysis centers can easily influence a patient's KtV by allowing a patient to dialyze longer. Vascular access related hospitalizations have a larger effect than cardiac related and all-cause hospitalizations.

The results from this section have a few interpretations. First, dialysis centers do influence patient utilization as measured by healthcare spending. When a patient switches to a new dialysis center, we observe a change in their utilization that is dependent on the utilization at their new center. Second, it is necessary to control for a patient's health when estimating the effects. While prior work can omit non-health factors (Finkelstein et al., 2016; Godøy and Huitfeldt, 2020; Fadlon and Parys, 2020), dialysis patients have a medical condition that inherently increases their utilization. By not controlling for health, we will attribute too much spending variation to the dialysis center rather than differences between patients due to health. Last, after controlling for a patient's health, dialysis centers have the most influence on spending that is plausibly under their control. For example, a dialysis center accounts for 89.4% and 52.8% of the variation in log total non-dialysis and log of physician and supplier spending, respectively, but only 19% in log of inpatient spending.

### 2.5.4 Dose Response

Figure 2.3 suggests that there may be a differential response depending on where $\Delta_i$ falls in the distribution. Additionally, dialysis patients with different levels of pre-switch spending are differentially responding to their change in utilization environment. I explore both of these possibilities in this section by first considering the distribution of $\Delta_i$. I divide $\Delta_i$ into equally

spaced quintiles and separately re-estimate Equation 2.4 for the bottom and top quintiles.[9] The event study plot from this estimation is shown in Figure 2.8. The bottom quintile has a mean of -0.258 and a standard deviation of 0.203; the top quintile has a mean of 0.374 and a standard deviation of 0.173. Most of the response is concentrated in the bottom quintile, as shown by the light red area. The top quintile estimates in light blue are noisy and not statistically significant in the post-switch years.

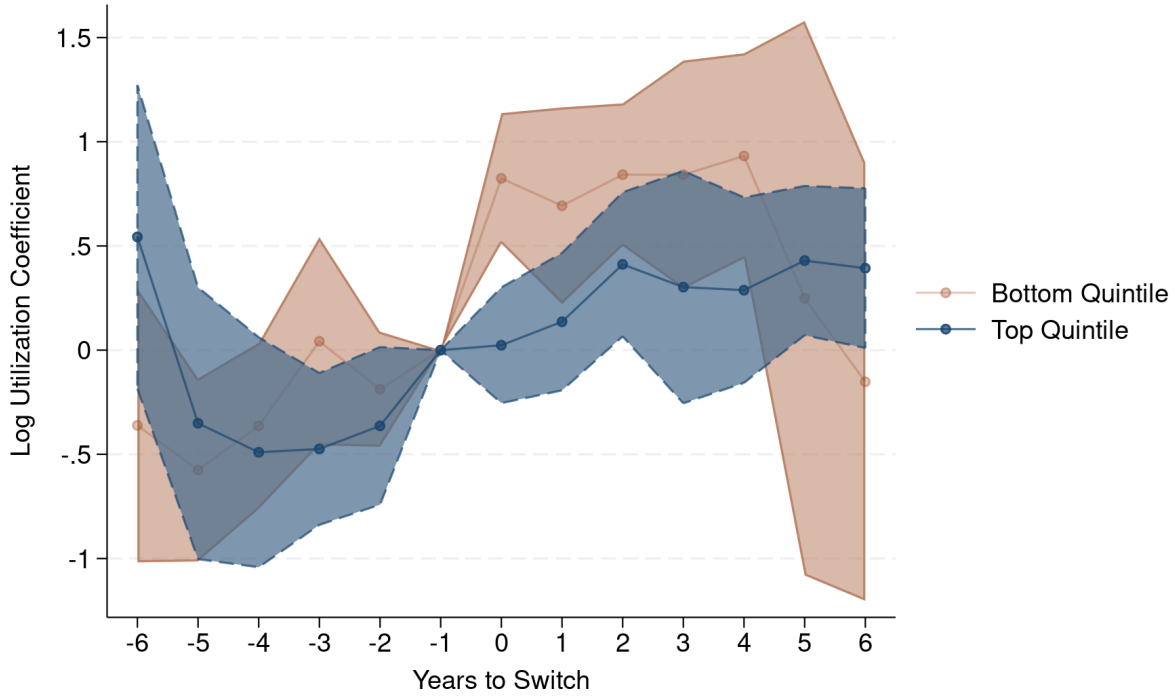



Figure 2.8 Top and Bottom Quintile of $\Delta_i$

Notes: Event study plot using quintiles of $\Delta_i$. The bottom (lowest) and top (highest) quintiles are shown. The bottom quintile has a mean of -0.258, a standard deviation of 0.203, and 33,819 patients. The top quintile has a mean of 0.374, standard deviation of 0.173, and 33,814 patients. The bottom quintile is the light red line and shows no pre-trends with an immediate jump following a switch. The effect is persistent for four years following a switch. Patients in the top quintile do not show any change upon a switch. Controls include 5-year age bins and whether a patient is hospitalized in a given year. Standard errors are clustered at the dialysis center level.

I next divide patients into whether they switch to a relatively higher spending ($\Delta_i > 0$) or relatively lower spending ($\Delta_i \leq 0$) dialysis center and re-estimate Equation 2.4. The results are

[9]The 2nd, 3rd, and 4th quintiles are not statistically significant pre-switch or post-switch, and the standard errors substantially overlap the bottom and top quintiles.

shown in Figure 2.9. The light blue shaded portion represents the estimation for patients that switch to a relatively higher spending dialysis center, and the light red are switches to a relatively lower spending dialysis center. Both types of switches exhibit no pre-trends in the years leading up to a switch. After a switch, patients going to a relatively lower spending dialysis center have a larger impact on their own spending, but patients at a higher spending dialysis center do not observe much of a change. Figures 2.8 and 2.9 suggest that lower utilization dialysis centers have a larger impact on patient spending than higher utilization centers. This could be for several reasons. For example, lower spending dialysis centers may be higher quality, and new patients experience an improvement in their health that reduces costly medical events. Medical services could also be viewed as an "opt-in" type of event, where patients have to actively choose to visit their nephrologist or undergo elective surgeries. Patients switching to lower utilization dialysis center may be less likely to opt in to discretionary medical services.

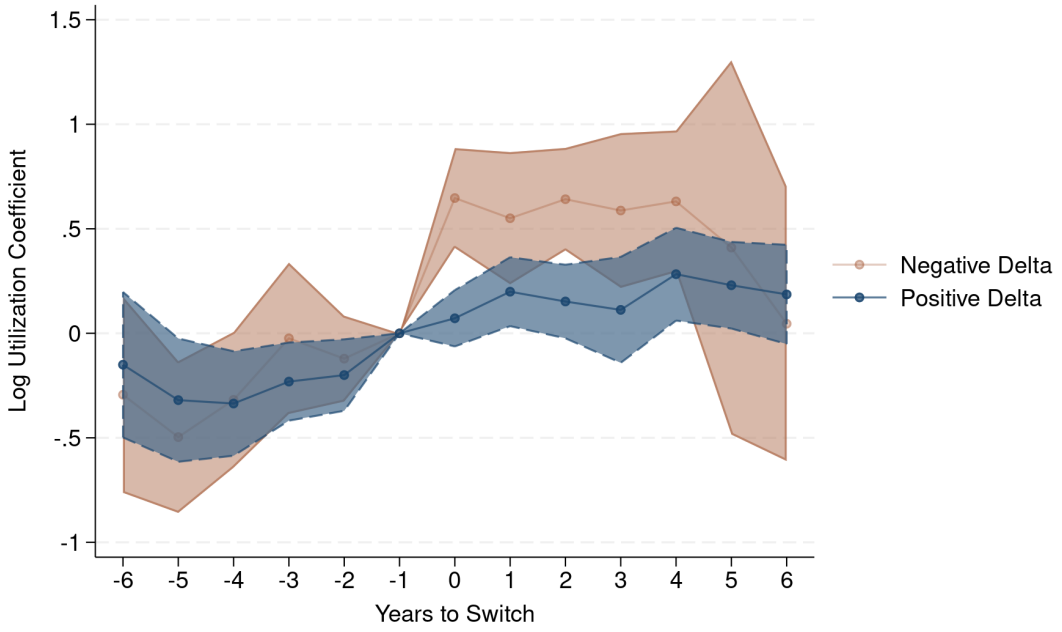



Figure 2.9 Positive and Negative Switches

Notes: Event study plot with patients switching to a dialysis center with higher spending than the origin (light blue) and lower spending than the origin (light red), representing a positive or negative $\Delta_i$, respectively. There are 100,397 patients with a positive switch, and 65,793 patients with a negative switch. Controls include 5-year age bins and whether a patient is hospitalized in a given year. Standard errors are clustered at the dialysis center level.

Last, I divide the sample into patients with spending prior to a switch that is higher or lower than the average at their origin dialysis center and separately re-estimate Equation 2.4. The results are show in Figure 2.10. The light blue shaded area are patients that have higher than average pre-switch spending, and the shaded light red are patients with pre-switch spending lower than the average at their origin dialysis center. The results are similar for both. Neither exhibit pre-trends, and both experience an immediate jump following a switch. Taken together with the previous estimations, a patient's change in utilization environment has a much larger effect on the progression of their own spending, rather than where a patient's spending is relative to the average.

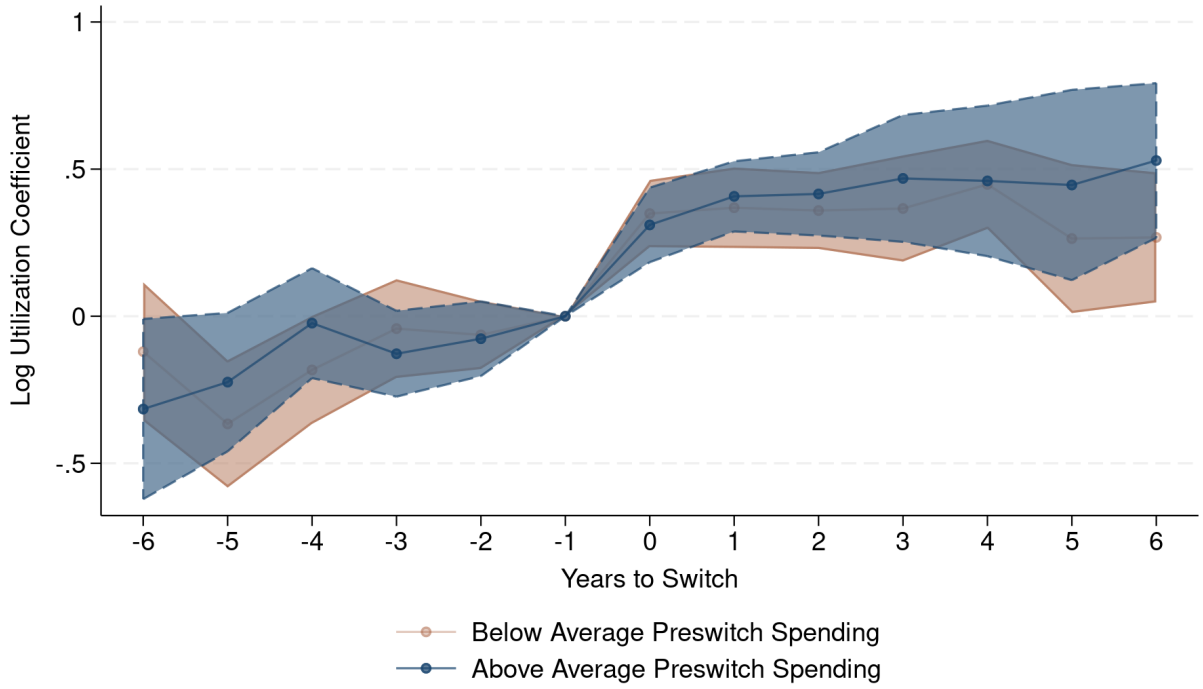



Figure 2.10 Pre-Switch Spending Relative to the Origin Dialysis Center's Average

Notes: Event study plot with patients switching to a dialysis center with higher spending than the origin (light blue) and lower spending than the origin (light red), representing a positive or negative $\Delta_i$, respectively. There are 100,397 patients with a positive switch, and 65,793 patients with a negative switch. Controls include 5-year age bins and whether a patient is hospitalized in a given year. Standard errors are clustered at the dialysis center level.

## 2.6 Conclusion

In this paper, I estimate how much influence a dialysis center has on the healthcare utilization of their patients. Since dialysis is a treatment that occurs three times per week, dialysis centers are uniquely positioned to encourage patients to seek out additional health services. I use patients that switch dialysis centers due to plausibly exogenous factors to identify the effects. I find that dialysis centers account for between 52% and 61% of the variation in total spending when not controlling for hospitalizations, depending on whether the log or level values of spending are used. This estimate drops to 37% and 39% when directly controlling for whether a patient is hospitalized in a given year, underscoring the importance of accounting for different levels of health status. These results highlight the importance of considering difference between dialysis centers when studying dialysis patient utilization.

From a policy perspective, understanding the determinants of health care spending among dialysis patients can lead to more targeted policies. In light of CMS's stated goal of reducing the costs associated with dialysis care, targeted policies will be more effective at achieving this goal. For example, policies aimed at reducing in-patient spending may be more effective if they are targeted towards patient behavior rather than dialysis center differences. Conversely, policies aimed at improving dialysis outcomes, such at dialysis adequacy, will be more effective if they target dialysis center heterogeneity rather than patient behavior.

# CHAPTER 3

# VALUE-BASED PURCHASING AND PAYMENT REDUCTIONS: DIALYSIS CENTER RESPONSE TO THE END STAGE RENAL DISEASE QUALITY INCENTIVE PROGRAM

## 3.1 Introduction

The dialysis industry has experienced rapid growth over the past several decades (Eliason et al., 2020; Grieco and Mcdevitt, 2017), driven primarily by an increasing prevalence of end-stage renal disease (U.S. Renal Data System, 2023). The Centers for Medicare & Medicaid Services (CMS) provides the lion's share of reimbursement for dialysis services. In 2012, CMS altered the reimbursement scheme for dialysis, shifting from a fee-for-service model to a prospective payment system and introducing value-based purchasing. These changes were intended to create stronger incentives for dialysis centers to prioritize patient outcomes and improve quality. Under a prospective payment system, dialysis centers are paid a fixed, bundled amount for each dialysis treatment, inclusive of all medications and resources used. With value-based purchasing, CMS withholds a percentage of all reimbursement if a center is low-quality. Whether dialysis centers respond to lower payment rates by improving quality is an open question. In this paper, I empirically explore this relationship and quantify improvements realized by dialysis centers when faced with a financial penalty.

The paradigm shift in payment is part of a larger emphasis on improving quality through the End Stage Renal Disease Quality Incentive Program (QIP). Patients undergoing dialysis are sensitive to low quality due to their tenuous health. The QIP began measuring several clinical outcomes, which are integrated into an annual total performance score. The performance score facilitates quality comparisons across different dialysis centers and within the same dialysis center over time. If a dialysis center scores below a predetermined threshold, it is assessed a payment penalty of between 0.5% and 2.0% of all reimbursement for Medicare beneficiaries for a full calendar year.

How dialysis centers respond to reduced payments via a performance penalty is initially

ambiguous. On the one hand, most dialysis centers are for-profit. Over 75% of dialysis patients use Medicare as the primary payer (Grieco and Mcdevitt, 2017; Eliason et al., 2020; Kepler et al., 2024), making Medicare the most common payer of dialysis services. A dialysis center treating 100 Medicare patients will lose between $15,000 and $60,000 if they are assigned a 0.5% or 2.0% payment reduction, respectively. On the other hand, quality may be sticky. Improving quality requires investments in capital and labor (Grieco and Mcdevitt, 2017), updating facility wide procedures (Eliason et al., 2020), or selectively treating high-quality patients (Bertuzzi et al., 2023). The financial incentives to improve quality may be lower than the costs associated with higher quality.

To estimate how centers respond to a payment reduction, I examine whether key outcome variables improve after a penalty assignment. I first present a difference-in-differences specification, defining dialysis centers that are assigned a payment penalty as the treated group. This specification compares penalized and non-penalized dialysis centers while controlling for time-varying characteristics as well as observed and unobserved heterogeneity across dialysis centers over time. I extend this specification to show how dialysis centers are reacting in the years leading up to and following a payment penalty. The event study specification allows me to indirectly test the crucial parallel trends assumption that identifies the causal effect of a payment penalty on clinical outcomes. Following the staggered difference-in-differences literature, I implement the estimator derived in Callaway and Sant'Anna (2021) (CS estimator) to remove inappropriate comparisons and estimate treatment effects based on the year in which a payment penalty is assessed.

My results suggest that dialysis centers are responsive to receiving a payment penalty. The difference-in-differences estimates point to measurable improvements in the hospitalization rate, mortality rate, and hospital readmissions. The dynamic event study specification suggests that dialysis center outcomes are relatively stable prior to a payment penalty, and experience a lasting improvement in the years following a penalty. Recent literature suggests that the standard two-way fixed-effects estimates may be biased under treatment timing heterogeneity, and from inappropriate comparisons between treated and already treated units (Callaway and Sant'Anna, 2021; Borusyak

et al., 2024). I repeat the same estimation specification using the methods derived in Callaway and Sant'Anna (2021). Under the CS estimator, I find larger effects for the septic hospitalization rate, number of patient deaths, and the standardized mortality rate. I find a slightly smaller but still statistically significant effect on the readmission ratio. These results show that dialysis centers are responsive to a payment penalty, suggesting that value-based purchasing in an effective mechanism to improve dialysis center quality.

The Quality Incentive Program was introduced in 2012 as CMS's first mandatory pay-for-performance program. Similar schemes have since been implemented, with varying levels of success. For example, the Hospital Readmissions Reduction Program (HRRP) penalizes hospitals for having above-average readmissions rates for Medicare patients. The HRRP is associated with lower mortality rates and reduced readmission rates for hospitals most affected by the program (Gupta, 2021). Mellor et al. (2017) similarly finds a reduction in hospital readmissions, with the effects more concentrated among patients admitted for a heart attack. These reductions may stem from changes in coding practices that occurred during the same period (Ibrahim et al., 2018; Ody et al., 2019). A second initiative, the Hospital Value-Based Purchasing (HVBP) program, rewards and penalizes hospitals for high and low-quality metrics, respectively. Norton et al. (2018) finds that hospitals respond by improving metrics with the greatest potential payoff, although the effect is non-linear with respect to different measures (Norton et al., 2023).

This paper contributes to three areas of research. The first contribution is to the quality disclosure literature. Public disclosure of ratings has been shown to increase quality and affect behavior. For example, disclosing physician patient ratings leads to improved physician performance (Eyring, 2020), but publicizing patient health outcomes can lead to patient sorting based on illness (Dranove et al., 2003). Godager et al. (2016) use experimental evidence to show that public disclosure of medical decision-making induces the provider to make patient welfare-maximizing choices.

Other fields find a similar relationship between quality disclosure and performance. Jin and Leslie (2003) examine the mandatory disclosure of restaurant hygiene quality report cards and find positive effects on health inspection scores, more sensitivity of consumer demand to hygiene

quality, and a decrease in food-borne illnesses. Their results suggest that restaurants implement changes to improve their hygiene quality. Oh and Park (2019) build a theoretical model in which nondisclosure of incumbent firm quality can be profitable and a deterrent for new entrants. The implementation of mandatory disclosure laws increases new firm entry and improves incumbent quality. I provide evidence that dialysis centers are responsive to measuring and disclosing quality, as reflected in the assignment of a payment penalty.

Second, I contribute to the literature that examines the relationship between financial penalties and quality. Value-based purchasing (VBP) programs are becoming increasingly popular with CMS and other large health insurance providers as a way to simultaneously reduce costs and improve quality. Under VBP programs, a healthcare provider is financially penalized for poor performance, providing incentives to either improve outcomes or change their patient population. Gupta (2021) studies the Hospital Readmissions Reduction Program (HRRP), which penalizes hospitals for high readmission rates among certain subsets of Medicare patients. They find that hospitals' responses to penalties account for about two-thirds of the decrease in hospital readmissions, with effects being divided between quality improvements and selective admissions through the emergency department. Norton et al. (2018) similarly find that the HRRP induces hospitals to improve their performance in areas with the highest marginal incentive. Further, hospitals with larger financial incentives generally improve more than hospitals with lower financial incentives. In the dialysis sector, Bertuzzi et al. (2023) use variations in the Quality Incentive Program to evaluate strategic dropping of patients that would decrease scores and induce a financial penalty. They find that patients who would reduce a facilities' score are more likely to switch facilities. My work expands on these studies by examining how assigned payment reductions influence future quality measures.

Last, I contribute to a growing literature evaluating the dialysis industry. Competition in the dialysis industry has been decreasing for the past three decades, with for-profit dialysis providers displacing non-profit dialysis providers (Wilson, 2016). Eliason et al. (2020) show that merging independent dialysis facilities with large chains leads to an increase in profit-maximizing behavior, which ultimately results in more hospitalizations and an increase in mortality. Additionally, dialysis

mergers are not always reviewed for antitrust violations, creating local duopolies or monopolies that result in higher hospitalizations and lower survival rates among affected patients (Wollmann, 2020).

Other work has examined dialysis quality in general (Grieco and Mcdevitt, 2017) and the Quality Incentive Program specifically (Bertuzzi et al., 2023; Kepler et al., 2024). Grieco and Mcdevitt (2017) suggests that dialysis centers face a quality-quantity trade-off, where it can increase patient volume by providing lower-quality dialysis to more patients, or focus on fewer patients while maintaining higher-quality care. Bertuzzi et al. (2023) finds that patients at dialysis centers near the penalty threshold are more likely to switch facilities, suggesting that centers may engage in cream-skimming to avoid penalties. Kepler et al. (2024) finds that new dialysis centers are more likely to enter low-quality markets and locate near dialysis centers with low scores. Additionally, physician referrals to low-quality dialysis centers decreases when scores are made public (Kepler et al., 2024). Ramanarayanan and Snyder (2012) shows how changing the threshold for designating a dialysis center based on expected mortality rates affects patient volume, suggesting that less-informed patients are more likely to receive treatment at low-ranking dialysis centers.

Two works similar to mine, Ajmal et al. (2020) and Griffin et al. (2023), both examine the relationship between quality scores and mortality. Ajmal et al. (2020) considers how mortality rates differ between dialysis centers in different bins of quality scores. They find a negative relationship between quality and mortality: dialysis centers with the lowest scores tend to have the highest mortality rates. But the study only considers scores quality in calendar year 2013 and may not extend to later years (Ajmal et al., 2020). Griffin et al. (2023) similarly look at mortality rates for dialysis centers assigned different levels of payment penalty. They find that a more harsh payment penalty is associated with higher mortality rates. Importantly, they show that dialysis centers that improve their score in the following year have concurrent reductions in mortality rates. I add to both of these works by extending the time frame to consider more years than Ajmal et al. (2020), while also considering other measures of quality, in addition to mortality rates (Griffin et al., 2023). I provide conferring evidence that dialysis centers respond to payment penalties, as measured by

the improvement of several key outcomes, with results robust to treatment timing heterogeneity.

The rest of the paper proceeds as follows. In section two, I provide institutional details about kidney failure and dialysis, and introduce the End Stage Renal Disease Quality Incentive Program. I describe the data in section three and outline my empirical specification in section four. Section five presents the results from three separate estimations: the canonical difference-in-differences; a dynamic event-study; and heterogeneous treatment effects similar to Callaway and Sant'Anna (2021). Section six concludes.

## 3.2 Institution Details

### 3.2.1 Kidney Failure and Dialysis

The kidneys filter waste, toxins, and excess fluid from the blood, and stimulate the production of red blood cells. Patients diagnosed with end-stage renal disease (ESRD) have kidneys that no longer adequately function. The primary treatment for ESRD is dialysis, which extends life expectancy and improves patients' quality of life. During dialysis treatment, blood is withdrawn from the body, filtered through a machine, and returned to the patient. The machine acts as a mechanical kidney, removing waste, toxins, and excess fluid that naturally build up over time. The blood is usually filtered several times over the course of three or four hours. Additionally, dialysis treatment introduces synthetic compounds normally produced in healthy kidneys, including erythropoietin, a necessary hormone that tells the body to produce red blood cells.

There are three types of dialysis treatment. The most common treatment is hemodialysis, which occurs at a dialysis treatment center and involves the patient being attached to a machine. Hemodialysis occurs three times per week, with each session lasting three to four hours. Because treatment is a frequent occurrence, patients tend to travel to the dialysis facility closest to their residence (Wollmann, 2020). The second type of dialysis treatment is peritoneal dialysis, which occurs every day and does not confine a patient to a machine. During treatment, patients introduce dialysis fluid into the peritoneal cavity to naturally absorb toxins. The fluid is drained after a few hours. Treatment can occur several times per day and requires patients to be relatively healthy. Peritoneal dialysis is not fully covered by CMS, imposing non-trivial out-of-pocket costs for patients.

The last type of dialysis is home dialysis. Home dialysis is a similar process to in-center dialysis, but instead relies on a smaller machine in the patient's home and occurs six to seven times per week. This treatment can be more expensive and is a less common option for patients with advanced kidney failure. In this paper, I only consider hemodialysis and refer to it simply as dialysis.

Dialysis markets are dominated by for-profit chains. Two of the largest chains, DaVita and Fresenius, operate well over 60% of all for-profit dialysis facilities and earn approximately 90% of the industry's revenue (USRDS, 2016; Eliason et al., 2020). These two chains account for the vast majority of mergers (Wilson, 2016) and have been subject to intense scrutiny for monopolistic behavior (Eliason et al., 2020). Quality at for-profit entities tends to be lower (Grieco and Mcdevitt, 2017), and patients are more likely to have higher hospitalization and mortality rates (Eliason et al., 2020).

### 3.2.2 CMS and the End Stage Renal Disease Quality Incentive Program

Since 1972, CMS has provided full benefits for all individuals diagnosed with ESRD regardless of age, contingent upon meeting the standard work requirements to qualify for Social Security, or have a spouse that meets the same requirements. Typically, Medicare coverage begins three months after diagnosis, following a mandatory three-month waiting period. Medicare is the primary payer if a patient is previously uninsured or has public insurance. If a patient is privately insured, Medicare begins as the secondary payer after the third month but switches to the primary payer after 30 months of treatment. The flexibility allows patients to continue to use their private health coverage to pay for dialysis but rely on Medicare to cover additional costs. In 2020, Medicare covered 64.0% of all new ESRD patients and 78.6% of all ESRD patients.[1]

Concerns about over-administering highly reimbursable drugs and an overall increase in the costs of dialysis prompted CMS to implement the End Stage Renal Disease Quality Incentive Program (QIP) in 2012. The QIP was part of a broader attempt to rein in Medicare costs through the Medicare Improvements for Patients and Providers Act (MIPPA) in 2008. Prior to 2012,

[1]Patients that have received a kidney transplant are still diagnosed with ESRD. Their Medicare coverage ends 36 months after a successful transplant. If a patient's kidney transplant fails in later years, Medicare coverage can be reinstated.

Medicare reimbursed dialysis facilities a flat rate for each dialysis session. Dialysis centers could then submit additional claims for injectable drugs administered during the course of treatment. Prior to the QIP, claims for highly reimbursable medications accounted for over 40% of the revenue for dialysis centers (Dai, 2014).

The QIP implemented two major changes. First, reimbursement moved from a fee-for-service model to a single prospective payment system. Dialysis centers are reimbursed with a bundled, per-treatment payment that includes all renal services furnished, medications, and biological products. A base rate is determined for each year and is case-mix adjusted for patient characteristics, in addition to facility-level adjustments for low patient volume, rural facilities, and a wage index.[2] Privately insured patients, in contrast, are reimbursed at a much higher rate than publicly insured patients. Using the largest geographic and case-mix adjustments, the highest possible rate paid by Medicare in 2019 was $1,081, whereas private insurance claims averaged $1,287 from 2012 to 2019 (League et al., 2022b).

The second change was the implementation of a value-based purchasing scheme, where dialysis centers are penalized for unsatisfactory performance. Dialysis centers are assigned an annual quality score based on several clinical and reporting outcomes. A payment penalty is assigned to centers scoring below a pre-determined score threshold. CMS uses lagged data when determining a performance score, with the whole process taking about four years. For example, in November 2011, CMS published the final rule governing the payment year (PY) 2014 measures which outlined the measures and scoring methods used to determine the performance scores. CMS collected data on dialysis care and outcomes in calendar year (CY) 2012 and generated scores. Dialysis firms were privately informed of their scores in 2013.[3] Performance scores were published in 2014 and patients treated in 2014 were subjected to the payment reduction assessed for the 2012 score.

CMS generates a dialysis center's performance score by calculating the share of patients at a facility that satisfy a particular standard. The share of patients meeting this standard are compared

[2]The base rate in CY 2023 is $264.09 and generally increases or decreases by 1 to 5% each year.

[3]Firms can request information about their scoring and submit one formal request to challenge their score.

to either the performance of the dialysis center in a previous year or the national standard, whichever results in a better score. A value of 10 is assigned if the center meets or exceeds the standard; the value decreases depending on how much worse the center performed. CMS assigns weights and adds each input to arrive at a standardized score.

In 2012 and 2013, dialysis centers could achieve a maximum score of 30. Starting in 2014, the maximum score was adjusted to 100 to accommodate a growing list of inputs used to calculate the score. I show the inclusion and removal of measures in Table 3.1. While the weights change from year to year, the basic method to calculate the total performance score remains the same. In the first two years of the program, CMS only considered hemoglobin above and below 12 g/dL and the urea reduction ratio, which is measure of how much waste is removed from the body over the course of a treatment. In 2013, the low hemoglobin measure is removed, and in 2014, CMS added a measure for how a dialysis center accesses a patient's blood.[4], as well as several reporting measures. The reporting measures are attestations of compliance, where a dialysis center affirms that they submitted the appropriate forms. The reporting measures include notifications of an infection and administering a patient survey. In 2019, CMS added a safety domain to emphasize the importance of monitoring infections. A more detailed description of the measures used is shown in Appendix Tables A.1 and A.2, and the method for calculating the score is further outlined in Appendix B.

[4]A fistula is the surgical fusion of a vein and an artery, and is considered the gold standard of vascular access. A fistula can withstand the pressure exerted on the body during treatment. A catheter is a tube that is inserted into an artery or vein and is less durable than a fistula. Additionally, a fistula is associated with a lower infection rate.

Table 3.1 Measures Added and Removed Each Year

| **Payment Year** | | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|---|---|---|---|
| **Clinical** | | | | | | | | | |
| Hemoglobin >12 g/dL | + | | | | | | | | |
| Hemoglobin <10 g/dL | - | | | | | | | | |
| Urea Reduction Ratio (URR) | + | | | | | | | | |
| AV Fistula | + | | | | | | | | |
| Catheter > 90 days | - | | | | | | | | |
| Kt/V Dialysis Adequacy | + | | | | | | | | |
| Hypercalcemia | - | | | | | | | | |
| Infections | - | | | | | | | | |
| Standardized Readmission Ratio | - | | | | | | | | |
| Standardized Transfusion Ratio | - | | | | | | | | |
| Patient Experience Survey | + | | | | | | | | |
| **Reporting** | | | | | | | | | |
| NHSN Event Reporting | | | | | | | | | |
| Patient Experience Survey | | | | | | | | | |
| Mineral Metabolism | | | | | | | | | |
| Anemia Management | | | | | | | | | |
| Pain Assessment | | | | | | | | | |
| Depression Screening | | | | | | | | | |
| Staff Flu Vaccination | | | | | | | | | |
| **Safety** | | | | | | | | | |
| NHSN Event Reporting | | | | | | | | | |
| Infections | - | | | | | | | | |

Notes: Measures included in quality scores are indicated with a green box. Measures that are not yet added or are removed are indicated with a gray box. The three domains included in the scores are "Clinical" which measures patient outcomes and lab values, "Reporting" which indicates whether a dialysis center submitted the appropriate forms to CMS, and "Safety" which combines two infection measures to emphasize their importance. Most years see the addition of measures. Measures are removed if they are topped-out. Two conditions must be met for an input to be removed. First, the 75th percentile, or 25th percentile for measures where lower percentiles indicate better performance, is indistinguishable from the 90th (10th) percentile. The 75th (25th) percentile is indistinguishable if it is within two standard errors of the 90th (10th) percentile. Second, the truncated coefficient of variation (TCV) is less than or equal to 0.10. The TCV is calculated by first removing the lower and upper 5th percentiles and then dividing the standard deviation by the mean of this truncated distribution.

Firms performing below a certain threshold are penalized for a full payment year, where CMS will withhold a percentage of all Medicare reimbursement. The minimum total performance score (mTPS) is calculated as the score a representative center would receive if they performed at the 50th

percentile for all metrics.[5] Eligible facilities[6] have their total performance score (TPS) calculated for each calendar year. The payment penalty starts at 0.5% and increases by 0.5 percentage points for every additional 10 points a center scores below the mTPS, with the maximum reduction set at 2.0%. Dialysis centers are not permitted to charge Medicare beneficiaries a higher price or separately bill for lost revenue.

### 3.3 Data

The data are sourced directly from The Centers for Medicare & Medicaid Services. I use information published on the End Stage Renal Disease Quality Incentive Program, which includes the total performance score and various clinical outcomes. Additionally, I use data from the Dialysis Facility Compare website and the Dialysis Facility Report, both of which include additional information on dialysis services, such as the number of dialysis stations; staffing levels; mortality rates, hospitalizations, and additional quality metrics. My analysis is performed at the center-year level.

I begin by showing descriptive statistics for dialysis centers from 2005 through 2019, encompassing seven years before and eight years after the implementation of the QIP. Table 3.2 shows pooled summary statistics for all dialysis centers. Approximately 86% of dialysis centers are for-profit, with 17.6 dialysis stations and 14.4 staff members serving about 105.7 unique patients over the course of a year. 78% of all patients have some type of Medicare coverage, which includes traditional Medicare (Part A and Part B), Medicare Advantage (Part C), dual enrollment of Medicare and Medicaid, and Medicare with commercial insurance. On average, patients are 63.5 years old. Additionally, 44% of patients are female, 28% are Black, 66% are white. Over 75% of all patients are currently seeing a nephrologist for their care. I define a dialysis market as the Hospital Service Area (HSA) a dialysis center resides within. The average market has 11.4 dialysis centers, and a Herfindahl-Hirschman Index (HHI) of 0.41, indicating that markets are concentrated. In total, there 8,597 unique dialysis centers and 86,643 dialysis center-years.

[5]The performance threshold for each measure is not the median score.

[6]To be eligible, a facility must have a minimum number of patients treated as well as a minimum number of patients with applicable values for the inputs into the performance score.

Table 3.2 Dialysis Center Characteristics

| | Mean | Std. Dev | 25th | Median | 75th |
|---|---|---|---|---|---|
| **Center Attributes** | | | | | |
| Profit Status (%) | 86.34 | 34.34 | 100.00 | 100.00 | 100.00 |
| Chain Affiliation (%) | 85.32 | 35.39 | 100.00 | 100.00 | 100.00 |
| Dialysis Stations | 17.63 | 8.33 | 12.00 | 17.00 | 22.00 |
| Total Staff | 14.47 | 8.86 | 9.00 | 12.00 | 18.00 |
| **Dialysis Types Offered** | | | | | |
| Offers Hemodialysis (%) | 96.76 | 17.70 | 100.00 | 100.00 | 100.00 |
| Offers Peritoneal Dialysis (%) | 48.57 | 49.98 | 0.00 | 0.00 | 100.00 |
| Offers Home Dialysis (%) | 24.17 | 42.81 | 0.00 | 0.00 | 0.00 |
| **Patient Characteristics** | | | | | |
| Total Patients | 105.78 | 67.68 | 58.00 | 93.00 | 139.00 |
| Medicare (%) | 78.82 | 15.94 | 70.11 | 83.23 | 90.84 |
| Non-Medicare (%) | 17.20 | 17.17 | 3.23 | 11.39 | 27.56 |
| Average Patient Age | 63.56 | 5.56 | 60.52 | 63.78 | 66.96 |
| Female (%) | 44.15 | 8.28 | 39.02 | 44.12 | 49.26 |
| Hispanic (%) | 13.15 | 20.14 | 0.00 | 4.76 | 17.39 |
| Black (%) | 28.08 | 27.19 | 5.56 | 18.92 | 45.46 |
| White (%) | 66.18 | 27.37 | 46.67 | 72.73 | 89.47 |
| Years on Dialysis | 4.57 | 1.13 | 3.82 | 4.51 | 5.24 |
| Patients Employed (%) | 18.92 | 17.21 | 5.56 | 16.00 | 28.00 |
| Number of Comorbidities | 3.10 | 0.78 | 2.58 | 3.04 | 3.55 |
| **Nephrologist Care** | | | | | |
| No Nephrologist (%) | 24.17 | 19.22 | 9.09 | 20.83 | 35.00 |
| Nephrologist $<$ 6 months (%) | 14.41 | 15.95 | 3.33 | 9.68 | 20.00 |
| Nephrologist 6-12 months (%) | 19.36 | 15.45 | 8.00 | 16.67 | 27.27 |
| Nephrologist $>$12 months (%) | 28.41 | 21.44 | 9.52 | 25.71 | 43.75 |
| **Market Concentration** | | | | | |
| HHI | 0.41 | 0.35 | 0.10 | 0.30 | 0.60 |
| Competitors | 11.47 | 18.56 | 2.00 | 4.00 | 13.00 |
| Unique Dialysis Centers | 8,597 | | | | |
| Center-Years | 86,643 | | | | |

Notes: This table shows summary statistics for dialysis centers from 2005-2019. Average, standard deviation, 25th, 50th, and 75th percentiles are shown. Observations are at the center-year level.

Table 3.3 shows dialysis centers characteristics from 2012-2019, based on the level of payment reduction. CMS assigns payment reductions on a sliding scale, from 0.5%, 1.0%, 1.5% and 2.0%,

depending on the level of deficiency. Profit status and chain affiliation are declining with the payment penalty level, suggesting that non-profit entities are more likely to be penalized at higher levels. While this is contrary to Grieco and Mcdevitt (2017) suggesting that for-profit dialysis centers are lower quality, for-profit centers may be better situated to respond to institutional changes, or have more resources to improve the measures that define the quality score. Dialysis stations, staffing levels, and patients treated are also declining with the level of payment reduction, although centers with a 0.5% payment penalty have higher levels than never penalized centers.

Table 3.3 Summary Statistics by Payment Reduction Level

| | No Reduction | 0.5% | 1.0% | 1.5% | 2.0% |
|---|---|---|---|---|---|
| **Center Attributes** | | | | | |
| Profit Status (%) | 88.73 | 86.61 | 84.45 | 82.05 | 74.41 |
| Chain Affiliation (%) | 90.94 | 85.37 | 78.42 | 71.08 | 57.70 |
| Dialysis Stations | 16.61 | 19.54 | 18.51 | 16.91 | 13.45 |
| Total Staff | 13.77 | 16.19 | 15.62 | 14.81 | 13.15 |
| **Patient Characteristics** | | | | | |
| Total Patients | 97.69 | 121.96 | 117.09 | 110.09 | 90.97 |
| Medicare (%) | 73.28 | 72.15 | 74.58 | 80.05 | 71.76 |
| Non-Medicare (%) | 25.55 | 26.62 | 23.72 | 17.46 | 25.05 |
| Average Patient Age | 63.85 | 63.46 | 63.05 | 63.58 | 63.86 |
| Female (%) | 43.17 | 43.63 | 43.92 | 44.13 | 43.27 |
| Hispanic (%) | 16.68 | 11.49 | 12.81 | 12.21 | 12.98 |
| Black (%) | 21.42 | 33.75 | 34.92 | 31.84 | 26.43 |
| White (%) | 70.80 | 61.63 | 60.32 | 63.90 | 69.21 |
| Years on Dialysis | 4.72 | 4.92 | 4.81 | 4.71 | 4.42 |
| Number of Comorbidities | 3.07 | 3.16 | 3.17 | 3.17 | 3.24 |
| **Market Concentration** | | | | | |
| HHI | 0.41 | 0.33 | 0.33 | 0.35 | 0.37 |
| Competitors | 11.45 | 16.00 | 16.76 | 14.90 | 14.31 |
| Dialysis Center-Years | 23,310 | 4,160 | 1,391 | 859 | 409 |

Notes: Provider-level characteristics for the years 2012-2019. Characteristics are shown for dialysis centers divided by annual payment reduction levels. Reduction levels include 0 (no penalty), 0.5%, 1.0%, 1.5% and 2.0%. Each observation is a center-year, allowing dialysis centers to belong to more than one column.

Outcomes of interest are shown in Table 3.4, separated by the level of reduction. The likelihood that a dialysis center is penalized next year, conditional on the reduction level this year, is lowest for centers that are not penalized, which is to be expected. If a dialysis center has a payment reduction of 0.5%, the likelihood that they are penalized again increases to 32.23%. The likelihood stays around 30% at all positive levels of a payment reduction. The survival category is a designation by CMS of how much better or worse a dialysis center's mortality rate is than expected.[7] Dialysis centers are given a designation of *worse than expected, as expected* and *better than expected* depending on how their mortality rate compares to the expected mortality rate.

Sepsis is a bloodstream infection common among patients with vascular access, including fistulas and catheters used for dialysis. Dialysis centers can directly affect infection rates by improving cleaning procedures, which is an indicator of quality (Patel et al., 2013; Grieco and Mcdevitt, 2017). The standard mortality and readmission ratios indicate how a dialysis center's mortality and readmission rates are relative to what is expected. Values equal to one indicate that the dialysis center had just as many deaths or readmissions as expected, whereas values greater (less) than indicate a higher (lower) rate than expected. The outcomes based on payment reduction are consistent with higher penalties being associated with declining quality. Relative to non-penalized centers, a higher payment reduction percent is correlated with worse survival, more hospitalizations for sepsis, and higher readmission and mortality ratios. These statistics are similar to Griffin et al. (2023), who finds worse outcomes for higher penalized centers. Additional summary statistics by penalty status before and after 2012 are shown in Appendix C.1.

[7] Ramanarayanan and Snyder (2012) offers a detailed explanation of the methodology used.

Table 3.4 Summary Statistics by Payment Reduction Level

| | No Reduction | 0.5% | 1.0% | 1.5% | 2.0% |
|---|---|---|---|---|---|
| Pr(Penalized Next Year) (%) | 9.80 | 32.23 | 34.72 | 23.91 | 30.19 |
| Survival Category | | | | | |
| Worse than Expected | 0.05 | 0.11 | 0.15 | 0.18 | 0.20 |
| As Expected | 0.85 | 0.83 | 0.81 | 0.77 | 0.75 |
| Better than Expected | 0.10 | 0.06 | 0.04 | 0.05 | 0.05 |
| % Hospitalizations for sepsis | 10.91 | 12.44 | 12.98 | 12.69 | 13.70 |
| Dialysis Patient Deaths | 10.67 | 13.79 | 13.49 | 13.22 | 11.46 |
| Standard Mortality Ratio | 0.97 | 1.05 | 1.10 | 1.11 | 1.14 |
| Standard Readmission Ratio | 0.94 | 1.04 | 1.08 | 1.07 | 1.11 |
| Dialysis Patients Kidney TX | 2.25 | 2.62 | 2.55 | 2.26 | 1.95 |
| Dialysis Center-Years | 23,310 | 4,160 | 1,391 | 859 | 409 |

Notes: Outcome variables of interest are shown for dialysis centers from 2012-2019, divided into the level payment reduction. Reduction levels include 0 (no penalty), 0.5%, 1.0%, 1.5% and 2.0%. An observation is a center-year, which allows dialysis centers to contribute to more than one column.

Next, I show descriptive statistics for the total performance score and payment penalties by separately regressing the total performance score and whether a dialysis center is assigned a payment penalty on a vector of observable characteristics. The results from these two regressions are show in Figure 3.1 and Figure 3.2, respectively. The coefficients are sorted by effect. A dialysis center's performance may be correlated with observable characteristics. For example, for-profit dialysis centers may engage in behavior to maximize profits over quality (Grieco and Mcdevitt, 2017), or are better equipped to respond to the institutional changes from the QIP. We may then expect profit status, among other attributes, to be a predictor of performance scores.

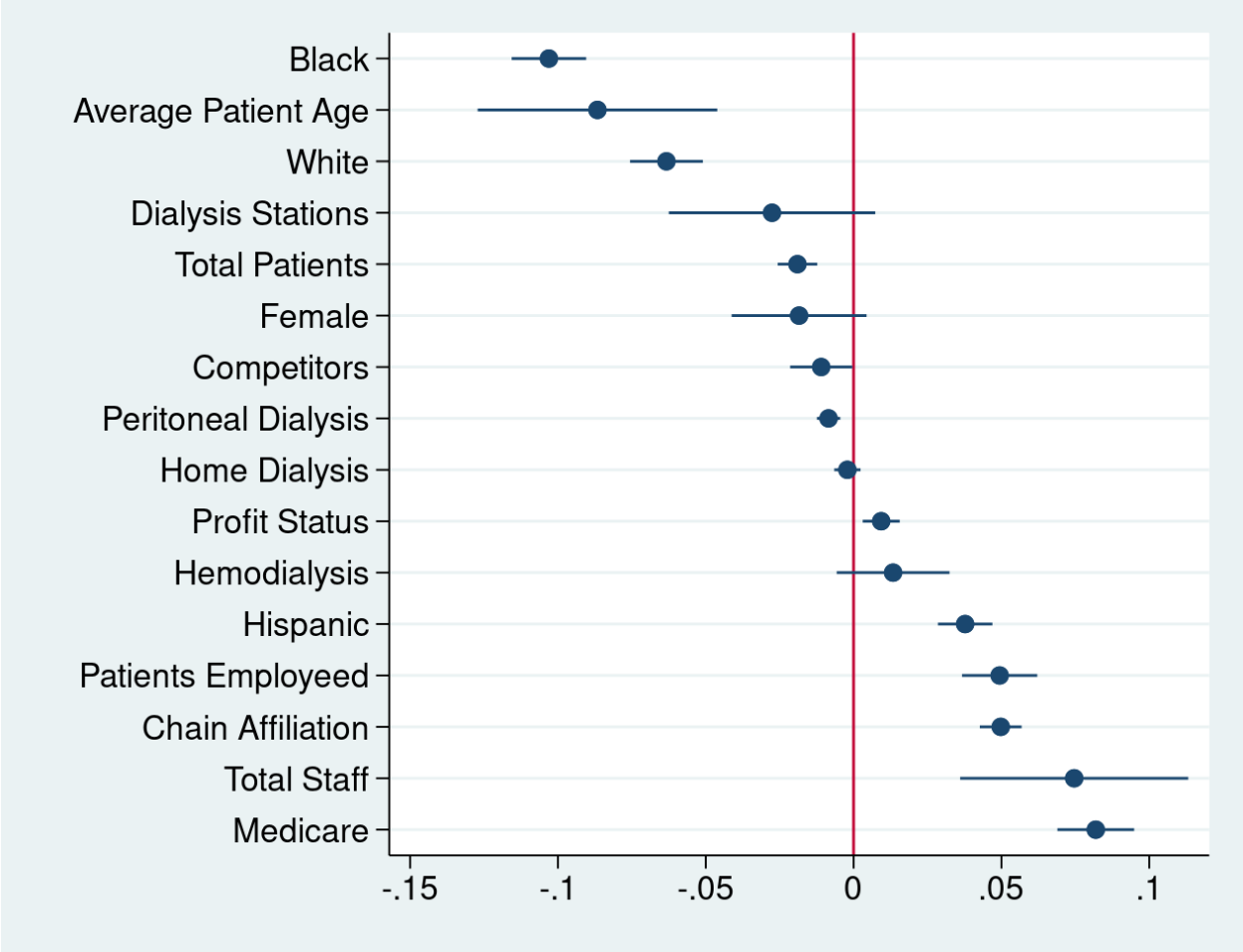



Figure 3.1 Effect of Dialysis Center Observable Characteristics on Performance
Notes: Coefficients are shown for a regression of the total performance score on dialysis center observables. Standard errors are clustered at the dialysis center level. The number of comorbidities (-0.435, se = 0.104), years on dialysis (0.385, se=0.096), and HHI (1.36, se = 0.305) are omitted from the plot but included in the estimate due to large effects.

The proportion of patients that are black or white, average patient age, the total number of dialysis stations, and whether the dialysis center offers peritoneal dialysis have negative effects on the performance score. On the other hand, profit status, percent Hispanic, percent employed, chain affiliation, the number of staff members, and the proportion of patients with Medicare coverage have positive effects on the score. The number of dialysis stations, percent female, the number of competitors, offering home dialysis and hemodialysis do not have an effect.

Next, I show the likelihood of being assigned a payment penalty as a function of the same observable characteristics using a logistic regression. The odds-ratios are shown in Figure 3.2.

The estimated effects are opposite to the performance score estimates, but this is expected: a lower performance score indicates a higher likelihood of being assigned a penalty.

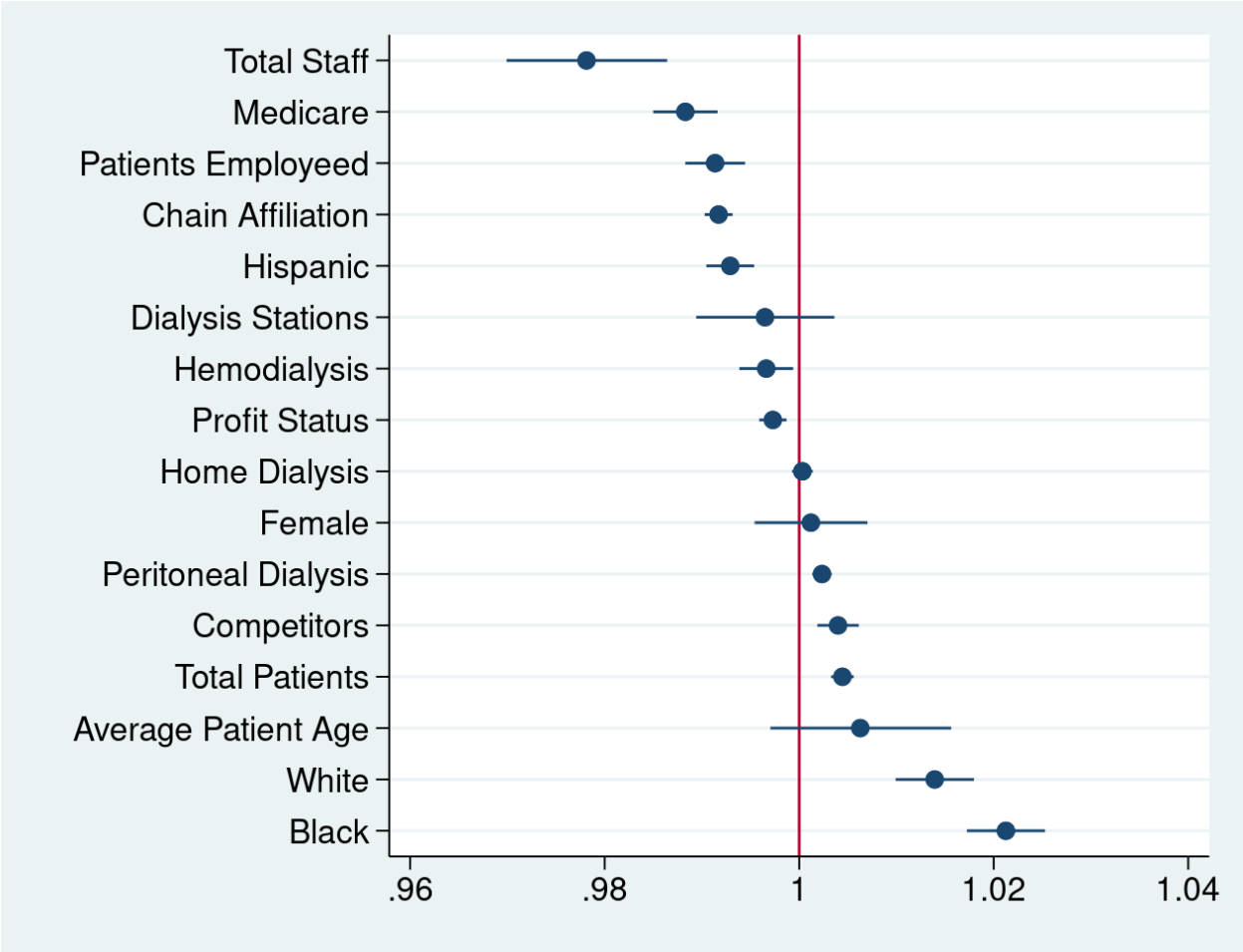



Figure 3.2 Effect of Dialysis Center Observable Characteristics on Likelihood of Payment Penalty
Notes: Coefficients are shown for a regression of a payment penalty on dialysis center observables. Standard errors are clustered at the dialysis center level. Number of comorbidities (1.077 se = 0.0279), years on dialysis (0.958, se=0.0228), and HHI (0.824, se = 0.0639) are omitted from the plot but included in the estimate due to large effects.

### 3.4 Empirical Specification

My empirical strategy relies on a difference-in-differences setup to estimate the effects of a payment penalty on dialysis center outcomes. I compare dialysis centers that are assigned a payment penalty to those that are not assigned a payment penalty. Under a parallel trends assumption, the differential change in outcomes between penalized and non-penalized dialysis centers can be interpreted as the causal effect of a payment reduction. The baseline specification

takes the following form:

$$Y_{i,t} = \alpha_0 + \delta_1(TreatPenalty_{i,t}) + \beta X_{i,t} + \gamma_i + \lambda_t + \varepsilon_{i,t} \tag{3.1}$$

where $Y_{i,t}$ is the outcome of interest for dialysis center $i$ in year $t$, $TreatPenalty_{i,t}$ is the interaction term of a binary $Post$ indicator that takes the value of 1 for the years after 2012, and a binary $Treated$ indicator that takes the value of 1 for dialysis centers assigned a payment penalty after 2012. $\mathbf{X}_{it}$ are time-varying dialysis center controls, including average patient demographics and dialysis center attributes such as the number of dialysis stations and staffing levels. $\gamma_i$ and $\lambda_t$ are dialysis center and year fixed-effects, respectively. The fixed-effects control for observed and unobserved heterogeneity between treated and control dialysis centers that is constant over time. The dialysis center fixed-effects also act to account for non-random assignment of a payment penalty. As shown in Table 3.4, dialysis centers that are assigned a penalty are different from those not assigned a penalty. Including dialysis center fixed-effects helps account for this non-random assignment by differencing out time-invariant factors within a given dialysis center (Gupta, 2021).

The identifying assumption underpinning Equation 3.1 is parallel trends: absent a payment penalty, a treated dialysis center would have progressed similarly as those without a payment penalty. This assumption rules out any external factors that would have differentially affected poorly performing dialysis centers that would not have also affected high performing dialysis centers. This could be the case, for example, if CMS were to invest extra money into low performing dialysis centers in the first year of low performance in an effort to improve metrics. While this assumption cannot be directly tested, I modify equation 3.1 to include lag and lead indicators and informally test the parallel trends assumption. The dynamic specification takes the form:

$$Y_{i,t} = \alpha_0 + \sum_{j=\underline{\tau}}^{-2} \delta_j \mathbf{1}(t - \tau_{penalty} = j) + \sum_{k=0}^{\overline{\tau}} \delta_k \mathbf{1}(t - \tau_{penalty} = k) + \beta X_{it} + \gamma_i + \lambda_i + \varepsilon_{i,t} \tag{3.2}$$

where the first summation terms equal 1 for the years $\{\underline{\tau}, -2\}$ prior to a payment reduction, and the second summation terms equal 1 for the years $\{0, \overline{\tau}\}$ after a payment reduction. I omit the year

prior to a payment penalty to use as a reference period. The $X_{i,t}$ term encompasses time-varying dialysis center characteristics, $\gamma_i$ and $\lambda_t$ are dialysis center and year fixed-effects, respectively. I informally test for parallel trends by evaluating whether the coefficients for the time periods prior to a payment penalty, $\delta_j$, are jointly not statistically significant.

Recent work in the difference-in-differences literature suggests that estimating Equation 3.2 may lead to biased estimates (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Borusyak et al., 2024). A primary issue is that the comparison group may be inappropriate, comparing treated groups to a combination of never-treated units, not-yet treated units, and units treated in a different time period. Goodman-Bacon (2021) suggests that the canonical two-way fixed-effects estimator is a weighted average of all possible two-by-two comparisons, and some comparisons can receive a negative weight. Callaway and Sant'Anna (2021) proposes an estimator that accounts for these possible combinations, and the fact that treatment effects will vary by treatment length and treatment timing.

In the context of this paper, a dialysis center with a payment penalty in 2012 may respond differently than a center penalized in 2018. Dialysis centers may also be more responsive to the threat of a penalty in later years as the resources to improve quality have time to develop. Their outcomes will therefore be different from those that are never-treated. The estimator proposed in Callaway and Sant'Anna (2021) (CS) separates treated units into groups based when treatment occurs. These groups are then pairwise compared to the untreated control group. The CS estimator eliminates so-called "forbidden" comparisons where the treated unit of interest is compared to earlier treated units (Callaway and Sant'Anna, 2021; Borusyak et al., 2024). Additionally, Callaway and Sant'Anna (2021) allow for the parallel trends assumption to hold after conditioning on relevant covariates. Table 3.4 suggests that penalized and non-penalized dialysis centers are different across several observable characteristics, highlighting the importance of this modification. I re-estimate Equation 3.2 using the proposed CS estimator and highlight differences between the two estimates.

## 3.5 Results

### 3.5.1 Canonical Difference-in-Differences

I present the results from the difference-in-differences estimation in Table 3.5. The top panel shows outcomes unrelated to mortality, namely the performance score, hospitalizations due to sepsis, the standardized readmission ratio, and kidney transplants. The bottom panel shows mortality related outcomes, such as the number of dialysis patient deaths, the standardized mortality ratio, and whether the survival category is *worse than expected* or *better than expected*. Once a dialysis center is treated, they remain in the treated group. The coefficient displayed is the $\delta_1$, and represents the effect of having an assigned payment penalty on the dependent variable, relative to those that are not treated, which includes not-yet and never-treated dialysis centers. Each estimation includes dialysis center and year fixed-effects, as well as time-varying facility characteristics.

The first column of the top panel in Table 3.5 shows the estimated effect of being in the treated group on the total performance score. The second column shows the effect on the percentage of hospitalizations due to a septic infection. The third column shows the effect on the standardized readmission ratio, where a higher number indicates a dialysis center has more hospital readmissions than expected. The last column shows the effect on kidney transplants. In the bottom panel of Table 3.5, I show estimations for mortality related outcomes. The first column shows the effect of being assigned a payment penalty on the total number of dialysis patient deaths. The second column uses the standardized mortality ratio as the outcome of interest. The third and fourth columns use whether a dialysis center has a mortality rate categorized as *worse than expected* or *better than expected*, respectively.

Table 3.5 Canonical Difference-in-Difference Estimates

| **Panel A: Clinical Outcomes** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | TPS | Septic Hospitalizations | Readmission Ratio | Transplants |
| Treated | -11.395*** | -0.353*** | -0.022*** | -0.111*** |
| | (0.254) | (0.089) | (0.004) | (0.037) |
| Observations | 30,892 | 48,138 | 48,012 | 48,130 |
| R-squared | 0.878 | 0.448 | 0.634 | 0.624 |

| **Panel B: Mortality Outcomes** | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Number of Deaths | Mortality Ratio | Survival Low Category | Survival High Category |
| Treated | -0.273*** | -0.019*** | 0.002 | -0.007 |
| | (0.079) | (0.006) | (0.006) | (0.006) |
| Observations | 48,184 | 47,515 | 44,872 | 44,872 |
| R-squared | 0.747 | 0.360 | 0.448 | 0.421 |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: Canonical difference-in-differences estimation of the effect of being assigned a payment penalty on the outcome variable two years after the penalty. All eight estimations include dialysis provider and year fixed-effects, as well as time-varying facility level characteristics.

In the first column, the total performance score shows a decline in the years following a penalty. As I show in Figure 3.3 in the top left panel, the performance score drops in year $t = 0$, thereby inducing a payment penalty. The performance score does improve to the same level as in the year prior to a penalty, but this is not captured in the static estimation because of the large drop in year $t = 0$. A dialysis center that is assigned a payment penalty exhibits an improvement in their septic hospitalization rate and readmission ratio. The percent of hospitalizations due to a septic infection decreases by 0.353 percentage points, and the readmission ratio decreases by 0.022 points. The number of kidney transplants decreases by 0.111 transplants per year, although there are numerous outside factors influencing whether a patient receives a transplant.

A penalized dialysis center will decrease the number of patient deaths by 0.273 deaths per year. The standardized mortality ratio will decrease by 0.019 in the years following a payment penalty. The likelihood that a dialysis center's survival category is *worse than expected* or *better than expected* does not have an appreciable change following a payment penalty, which could be due to CMS using a rolling four-year average for the predicted and observed mortality rates.

### 3.5.2 Event Study

The previous section uses year $t$ as the year a dialysis center's improvement is observable, but it could be the case that dialysis centers are responding to a payment penalty in later years. I informally test the parallel trends assumption by replacing the treated indicator for a binary variable set equal to 1 if a dialysis center is penalized in year $t$ and 0 otherwise. I interact this penalty indicator with relative time dummies, which are set equal to 1 for $j$ years prior and $k$ years following a payment penalty. I omit the year prior to a payment penalty being assigned, and truncate the results to six years prior and six years following the payment penalty, showing how dialysis centers respond in the years prior to and after a payment penalty.

I again group the results into non-mortality and mortality related outcomes. The estimates for the first group are shown in Figure 3.3. The specification is the same as panel A in Table 3.5, except with an interaction of the treatment variable with a relative time indicator. In the top left panel, I show how the performance score progresses in the time periods before and after a payment penalty. The top right panel shows the progression of the percent of hospitalizations that are due to a septic infection. The bottom left panel shows how the standard readmission ratio changes for penalized, and the bottom right panel shows how kidney transplants progress.

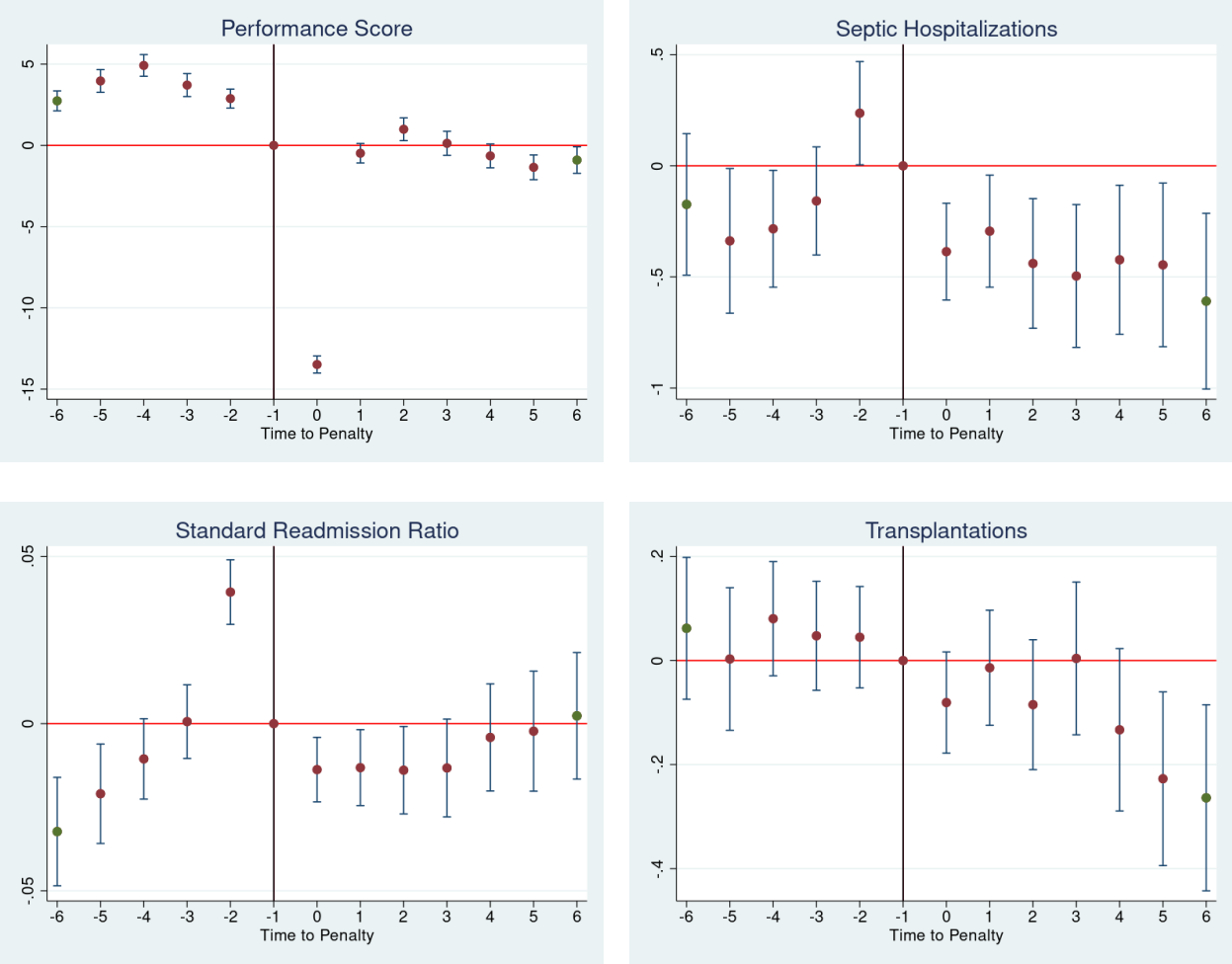



Figure 3.3 Event Study Coefficients for Non-Mortality Outcomes

Notes: Dynamic difference-in-differences estimation using non-mortality related outcomes. The empirical specification is identical to Table 3.5 with an interaction between a treatment indicator and a relative time dummy variable. All specifications include dialysis center and year fixed-effects, as well as time-varying dialysis center characteristics. Standard errors are clustered at the dialysis center level. The reference year is the year prior to the assignment of a payment penalty.

The top left panel of Figure 3.3 shows that the performance score leading up to a payment penalty is generally higher, then precipitously drops in year $t$ when a dialysis center is penalized. Following the penalty, the score rebounds to a level slightly lower than the score in year $t-1$ and stays relatively persistent. Hospitalizations due to sepsis show a spike in year $t-2$, which is the year data is collected for the performance score in year $t$, as shown in the top right panel of Figure 3.3 Following a payment penalty, the septic hospitalization rate decreases and stays negative for at least six years, suggesting a sustained improvement. The standardized readmission ratio in the

bottom left panel exhibits an upward trend prior to a payment penalty, a spike in year $t-2$, and then a leveling off in the following years. Kidney transplants, which are shown in the bottom right panel, have a slight downward trend without a noticeable change after a payment penalty.

The second group of results shows outcomes related to mortality, which I present in Figure 3.4, following the same estimation as panel B in Table 3.5. The top left panel in Figure 3.4 shows the effect of a payment penalty on the number of dialysis patient deaths. The top right panel shows the effect of a payment penalty on the standardized mortality ratio. The bottom panels show how the survival category changes for a dialysis center, with the bottom left representing the likelihood a center's mortality rate is categorized as *worse than expected* and the bottom right representing the likelihood of the mortality rate being categorized as *better than expected*.

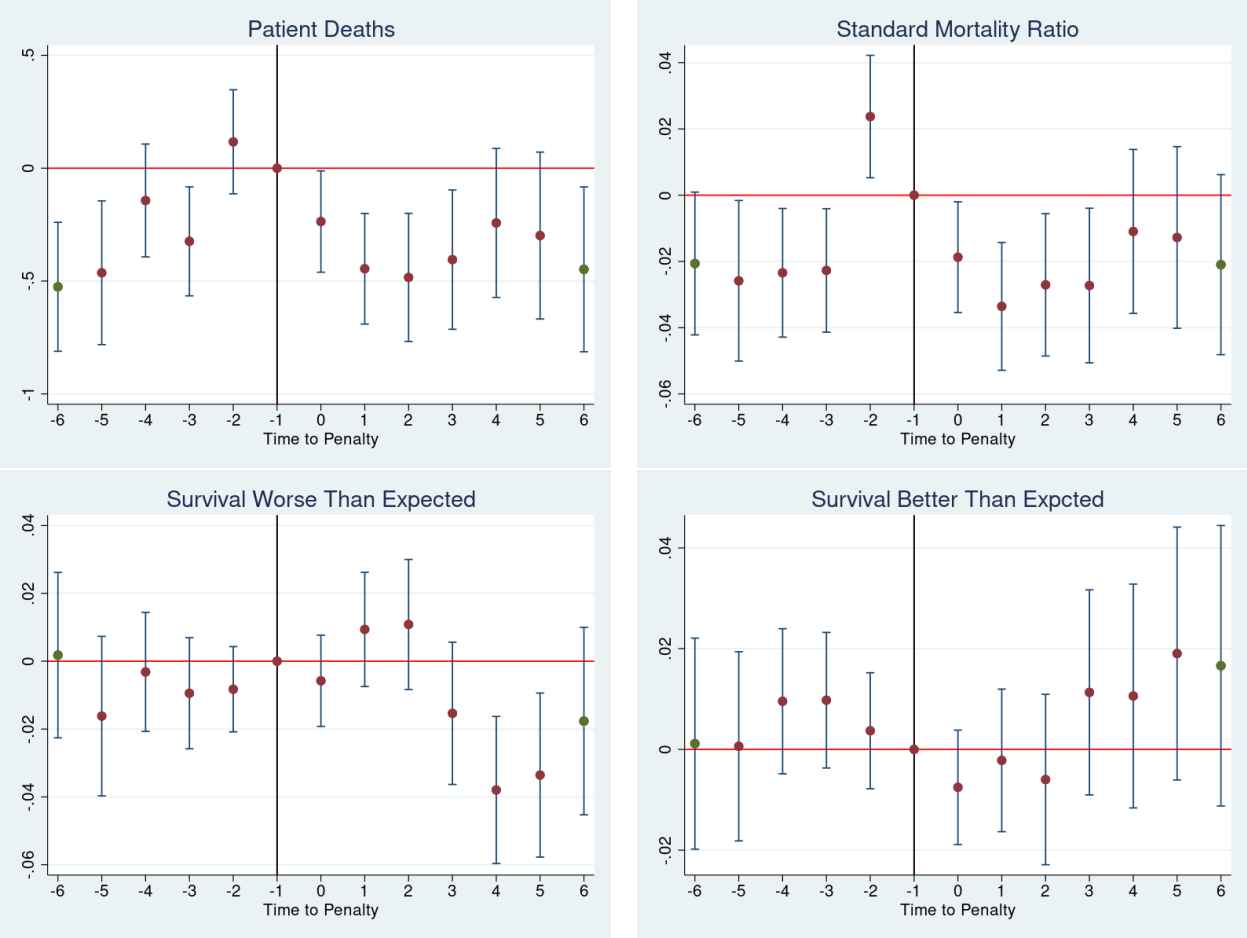



Figure 3.4 Event Study Coefficient Plots

Notes: Dynamic difference-in-differences estimation using mortality related outcomes. The empirical specification is identical to Table 3.5 with an interaction between a treatment indicator and a relative time dummy variable. All specifications include dialysis center and year fixed-effects, as well as time-varying dialysis center characteristics. Standard errors are clustered at the dialysis center level. The reference year is the year prior to the assignment of a payment penalty.

The number of dialysis patient deaths are trending upwards slightly in years before payment penalty until year $t-2$, which is the year a center performs low enough to receive a penalty. The coefficients after a payment penalty are negative and statistically significant for at least four years. The standard mortality ratio is barely negative in the years prior to a penalty and shows a spike in year $t-2$. Then, for at least four years after a penalty, the estimates are negative and statistically significant, suggesting an improvement in the standard mortality rate. The likelihood a dialysis center has a survival category of *worse than expected* shows very little pre-trends prior to a payment penalty, then a decline starting in year $t+3$. There does not appear to be a change in the likelihood

of having a survival category of *better than expected* for penalized dialysis centers.

Overall, the results are consistent with dialysis centers responding to a payment penalty. The percent of hospitalizations, standardized mortality ratio, and whether the survival category is worse than expected all show an improvement in the years following a penalty, with small pre-trends prior to the penalty. One thing to note about these estimates is the presence of a sharp jump in the dependent variable in year $t-2$. This is consistent with an Ashenfelter dip and not all surprising (Heckman and Smith, 1999). Low performing dialysis centers are assigned a payment penalty, and the year in which data is used to assess a penalty will show a poor performance.

### 3.5.3 Differential Treatment Timing

Given that treatment can occur in any year starting in 2012, the results of the previous section may be biased if dialysis centers respond differently in later years. This could be the case if dialysis centers adapt to the program as they gain experience. Another complication could arise if treated dialysis centers are compared to the wrong control group, e.g. a combination of never, not yet, and already treated (Callaway and Sant'Anna, 2021). I account for this by re-estimating Equation 3.2 using the Callaway Sant'Anna (CS) method derived in Callaway and Sant'Anna (2021). In their work Callaway and Sant'Anna (2021) suggest allowing cohort and treatment timing heterogeneity by creating group-time average treatment effects. The CS estimator is robust to allowing parallel trends to hold after conditioning on covariates, and allows dialysis centers to anticipate a payment penalty before it goes into effect. I use the untreated (not yet treated and never treated) group as the control group, and define a cohort as dialysis centers assigned a penalty in year $t$.

I begin by showing the average treatment effect on the treated (ATT) for the eight dependent variables from Table 3.5. I combine all coefficients in Table 3.6, along with the same coefficients from the canonical two-way fixed-effects difference-in-difference estimations. The reference period is the year prior to the assignment of a payment penalty. Standard errors are clustered at the dialysis center level. I additionally show the corresponding event study plots in Figures 3.5 and 3.6.

The first column of Table 3.6 shows the effect on the performance score after the assignment of a payment penalty. The second and third columns show the percentage of hospitalizations due

to a septic infection and the standard readmission ratio, respectively. The fourth column shows the effect on the number of kidney transplants. Columns five through eight are mortality outcomes, specifically the number of dialysis patient deaths, the standardized mortality ratio, and the likelihood of having a survival category worse than expected or better than expected, respectively.

Table 3.6 Callaway Sant'Anna Estimates

| **Panel A: Clinical Outcomes** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | TPS | Septic Hospitalizations | Readmission Ratio | Transplants |
| ATT | -6.622*** | -0.500*** | -0.018** | -0.176** |
| | (0.329) | (0.125) | (0.006) | (0.069) |
| DiD Estimate (Table 3.5 Panel A) | -11.395*** | -0.353*** | -0.022*** | -0.111*** |
| | (0.254) | (0.089) | (0.004) | (0.037) |

| **Panel B: Mortality Outcomes** | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Number of Deaths | Mortality Ratio | Survival Low Category | Survival High Category |
| ATT | -0.413* | -0.026*** | -0.011 | 0.001 |
| | (0.237) | (0.007) | (0.009) | (0.008) |
| DiD Estimate (Table 3.5 Panel B) | -0.273*** | -0.019*** | 0.002 | -0.007 |
| | (0.079) | (0.006) | (0.006) | (0.006) |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: Estimate using Callaway and Sant'Anna (2021). Untreated dialysis centers are the control group. The average treatment effect on the treated is shown for each column. All estimates have dialysis center and year fixed-effects.

Beginning with the performance score in the first column, the CS estimation suggests that the effect is nearly cut in half. Again, the explanation being that the quality score induces a penalty, so the fact that the score is lower is not unexpected. The other columns show a similar point estimation between the CS estimate and two-way fixed-effects estimations. The effect on the septic hospitalization rate is slightly larger for the CS estimate, 0.500 to 0.353, suggesting that dialysis centers improve their septic hospitalization rate following a payment penalty. The effect on the

standardized readmission ratio is smaller in magnitude for the CS estimate compared to the TWFE estimate, -0.018 to -0.022, and slightly larger for kidney transplants (-0.176 to -0.111). The number of dialysis patient deaths and the standardized mortality ratio also have a larger effect with the CS method compared to the TWFE estimates. I still find the survival categories to be unresponsive to the payment penalty, although Figure 3.4 and 3.6 in the bottom panels suggest that the effect may take a few years to manifest.

I plot the event study estimates for the non-mortality related dependent variables in Figures 3.5. The performance score, shown in the top left panel of Figure 3.5, exhibits a similar trend as the previous event study plot. The performance score precipitously drops in year $t = 0$ and then rebounds to a level slightly below the score before a payment penalty. The percentage of hospitalizations due to a septic infection (top right), standardized readmission ratio (bottom left), and number of kidney transplants (bottom right) all suggest that the parallel trends assumption may hold. Additionally, the plots suggest that there is a small but statistically significant improvement in the years following a payment penalty.

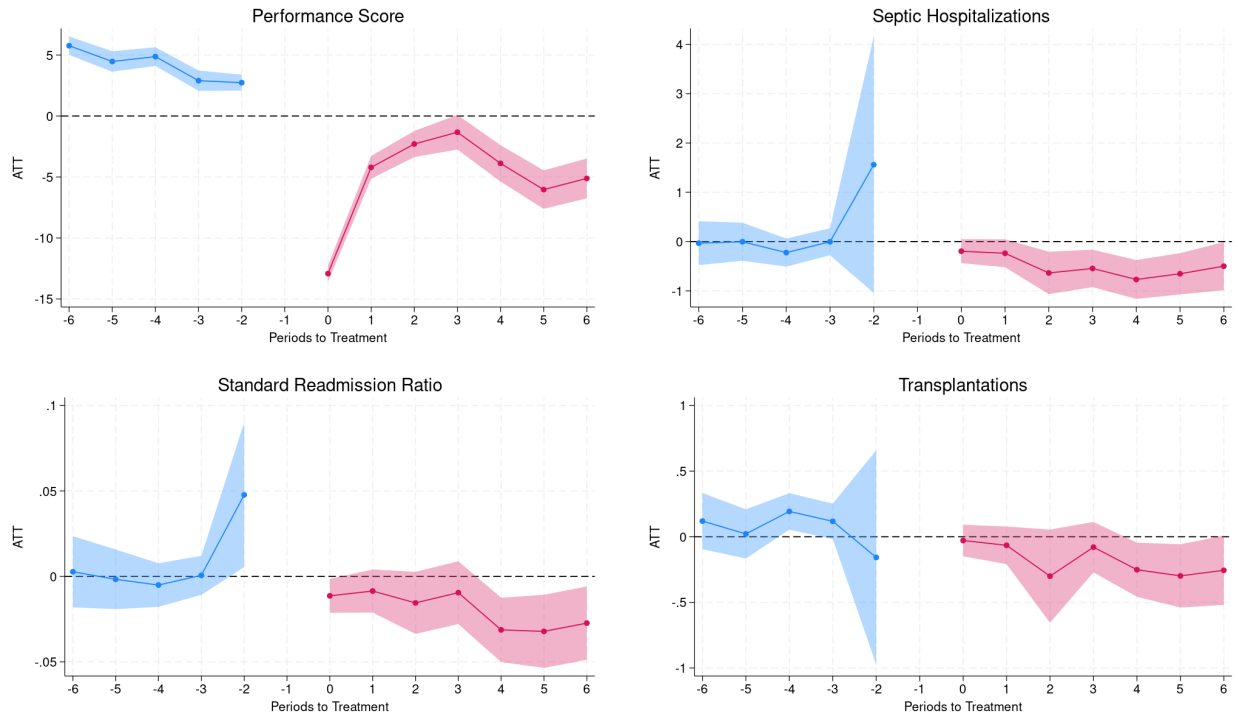



Figure 3.5 Callaway Sant'Anna Estimation Method Coefficient Plots, Non-Mortality Outcomes
Notes: Event study plot from the Callaway Sant'Anna estimate. The reference year is the year prior to a payment penalty being assigned. Non-mortality related outcomes are used as the dependent variable. Time-varying dialysis center controls are included in the regression, in addition to dialysis center and year fixed effects. Standard errors are clustered at the dialysis center level.

Next, I show the event study plots for mortality related outcomes in Figure 3.6. The number of dialysis patient deaths are shown in the top left panel; the standardized mortality ratio is shown in the top right panel; and a survival category of *worse than expected* and a survival category of *better than expected* are shown in the bottom left and bottom right panels, respectively. All four estimates are similar to their canonical two-way fixed-effects event study counterpart. The effect on the number of patient deaths is small and takes a few years to develop. The standardized mortality ratio, on the other hand, has an immediate decline in the years following a payment penalty. The *worse than expected* survival category shows a small improvement (decline) starting four years after a payment penalty, with the *better than expected* survival category not showing any improvement.

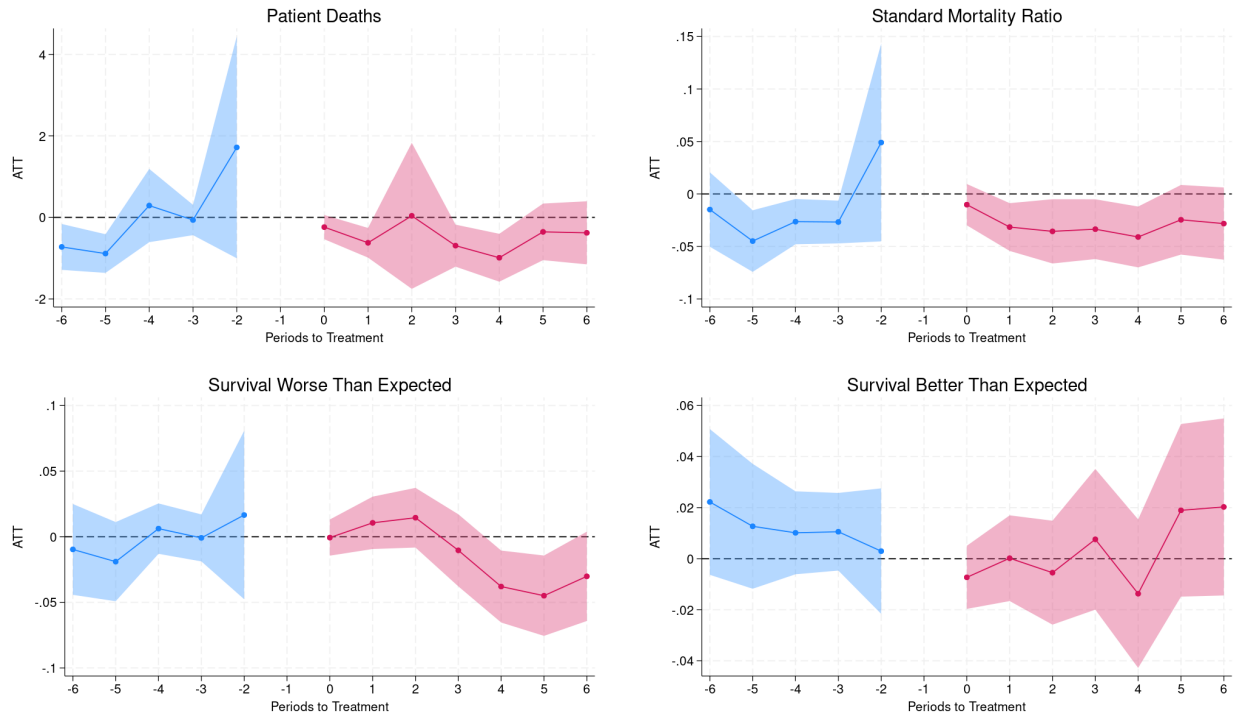



Figure 3.6 Callaway Sant'Anna Estimation Method Coefficient Plot, Mortality Related Outcomes
Notes: Event study plot from the Callaway Sant'Anna estimate. The reference year is the year prior to a payment penalty being assigned. Mortality related outcomes are used as the dependent variable. Time-varying dialysis center controls are included in the regression, in addition to dialysis center and year fixed effects. Standard errors are clustered at the dialysis center level.

### 3.5.4 Dose-Response to Payment Penalties

Dialysis centers may respond differentially depending on the level of penalty. To see if this is the case, I estimate the effect of a payment penalty using the CS estimator and canonical two-way fixed effects while imposing two sample restrictions. I first estimate the effect of a payment penalty for those with a 0.5% reduction by comparing them to centers without a payment penalty. The 0.5% reduction group is the largest penalized group, accounting for over 60% of the 6,819 penalties assigned. The second estimate compares centers with a 1.0%, 1.5%, or 2.0% reduction to those without a payment penalty. I estimate the effect on four variables: performance scores (TPS), septic hospitalizations, readmission ratio, and mortality ratio.

The results are shown in Table 3.7. The first column shows the estimates using the full sample of dialysis centers, which are from Table 3.6. The second column compares those with a 0.5%

penalty to those without a penalty, while the third column compares centers with a 1.0%, 1.5% and 2.0% penalty to centers that are not penalized.

Table 3.7 Dose-Response of Payment Penalties

| | All Centers | No Reduction and 0.5% | No Reduction and 1.0%, 1.5%, 2.0% |
|---|---|---|---|
| **TPS** | | | |
| CS ATT | -6.622*** | -4.996*** | -3.624*** |
| | (0.329) | (0.316) | (0.405) |
| DiD TWFE | -11.395*** | -9.364*** | -7.446*** |
| | (0.254) | (0.245) | (0.400) |
| **Septic Hospitalizations** | | | |
| CS ATT | -0.500*** | -0.473*** | -0.500*** |
| | (0.125) | (0.164) | (0.136) |
| DiD TWFE | -0.354*** | -0.301** | -0.365*** |
| | (0.089) | (0.121) | (0.102) |
| **Readmission Ratio** | | | |
| CS ATT | -0.018*** | -0.015** | -0.016** |
| | (0.006) | (0.007) | (0.006) |
| DiD TWFE | -0.022*** | -0.037*** | -0.021*** |
| | (0.004) | (0.006) | (0.005) |
| **Mortality Ratio** | | | |
| CS ATT | -0.026*** | -0.036*** | -0.026** |
| | (0.009) | (0.013) | (0.010) |
| DiD TWFE | -0.019*** | -0.033*** | -0.019*** |
| | (0.006) | (0.009) | (0.007) |

Standard errors are clustered at the dialysis center level
*** p<0.01, ** p<0.05, * p<0.1

Notes: Estimate using Callaway and Sant'Anna (2021). Untreated dialysis centers are the control group. The average treatment effect on the treated is shown for each column. All estimates include dialysis center and year fixed-effects.

There is mixed evidence that centers with larger penalties have a bigger response than those with smaller penalties. The first row shows the effect on the quality score. The decreasing magnitude suggests that higher penalized centers improve the performance score more, but could also reflect mean reversion or a lower marginal cost to improve a score at the lower end of the distribution. The second row shows the effect on septic hospitalizations. Both the CS estimator and two-way fixed effects estimate show a larger magnitude for higher penalized centers, suggesting that these centers improve more than centers penalized at the 0.5% level. The third row, showing the effect on

the readmission ratio, suggests that the response is the same between the two penalty groups when using the CS estimator, but the 0.5% reduction group has a larger improvement when estimated via TWFE: -0.037 to -0.021. The last row uses the standard mortality ratio as the dependent variable. Both estimators suggest that the 0.5% group has a larger improvement than the 1.0% to 2.0% group: -0.036 to -0.026 via the CS estimator, and -0.033 to -0.019 via the TWFE estimator. Overall, Table 3.7 suggests that higher penalized centers might improve more than lower penalized centers along some dimensions, but this is not a universal response.

## 3.6 Conclusion

In this paper, I estimate how dialysis centers respond to being assessed a payment penalty by the End Stage Renal Disease Quality Incentive Program. Payment penalties are assigned to dialysis centers with quality scores below a predetermined threshold. If dialysis centers are not responsive to the penalty, then the payment reduction may not be an effective mechanism to improve dialysis center outcomes or improve quality. I show that the canonical difference-in-differences and relatively new staggered treatment timing estimators give similar results across several outcomes of interest. The Callaway and Sant'Anna (2021) estimates are slightly larger in magnitude than the two-way fixed-effects estimates, suggesting that the results are robust to differential treatment timing.

While the estimates are similar, neither appropriately addresses the immediate jump of the outcome variable the year data is collected, similar to an Ashenfelter dip (Heckman and Smith, 1999). This is a feature of the data, rather than a bug: dialysis centers assigned a payment penalty have poor performance in year $t - 2$. My estimates provide evidence that dialysis centers are responsive to a payment penalty, as measured by several outcomes. Addressing the Ashenfelter dip is a necessary next step to more accurately assess the true impact of the QIP on dialysis center performance.

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# APPENDIX A

# APPENDIX TO CHAPTER 1

## A.1 Measure Definitions

Table A.1 Definitions for Clinical Metrics for Dialysis Facilities

| Clinical | |
|---|---|
| Hemoglobin >12 g/dL | Percentage of eligible Medicare dialysis patients with a mean hemoglobin value greater than 12.0 g/dL. |
| Hemoglobin <10 g/dL | Percentage of eligible Medicare dialysis patients with a mean hemoglobin value less than 10.0 g/dL. |
| Urea Reduction Ratio (URR) | The percentage of eligible Medicare in-center hemodialysis patients with a median urea reduction ratio (URR) of at least 65%. |
| AV Fistula | Percentage of months where an arterial venous (AV) fistula was in use for adult hemodialysis patients. |
| Catheter > 90 days | Percentage of months where an intravenous catheter was in use for 90 days or more for adult hemodialysis patients. |
| Kt/V Dialysis Adequacy | Percent of hemodialysis patient-months with spKt/V greater than or equal to 1.2. |
| Hypercalcemia | Proportion of patient-months with a 3-month rolling average of total uncorrected serum calcium greater than 10.2 mg/dL. |
| Infections | Number of hemodialysis outpatients with positive blood cultures per 100 hemodialysis patient-months. |
| Standardized Readmission Ratio | Standardized hospital readmission ratio of the number of observed unplanned readmissions to the number of expected unplanned readmissions. |
| Standardized Transfusion Ratio | Risk-adjusted transfusion ratio (STrR) for all adult Medicare dialysis patients. STrR is a ratio of the number of observed eligible red blood cell transfusion events occurring in patients dialyzing at a facility to the number of eligible transfusions that would be expected from a predictive model that accounts for patient characteristics within each facility. |
| Patient Experience Survey | Percentage of patient responses to multiple testing tools. Composite score: The proportion of respondents answering each of the response options for each item, summed across the items within a composite to yield the composite measure score. (Nephrologists' Communication and Caring, Quality of Dialysis Center Care and Operations, Providing Information to Patients.) |

Notes: This table presents definitions for various clinical outcomes used in the total performance score each year.

Table A.2 Definitions for Reporting Metrics for Dialysis Facilities

| **Reporting** | |
|---|---|
| NHSN Event Reporting | Number of months for which the facility reports National Healthcare Safety Network (NHSN) Dialysis Event data to the Centers for Disease Control and Prevention. |
| Patient Experience Survey | Attestation that the facility administered the survey. |
| Mineral Metabolism | Number of months for which the facility reports serum calcium and phosphorus for each Medicare patient. |
| Anemia Management | Number of months for which the facility reports erythropoiesis-stimulating agents dosage (as applicable) and hemoglobin/hematocrit for each Medicare patient. |
| Pain Assessment$^{\alpha}$ | Facility reports in CROWNWeb one of the six conditions for each qualifying patient once before August 1 and February 1 of the following year. |
| Depression Screening$\alpha$ | Facility reports in CROWNWeb on the six conditions below for each qualifying patient once before February 1 of the following year. |
| Staff Flu Vaccination | Facility submits Healthcare Personnel Influenza Vaccination Summary Report to CDC's NHSN system. |
| $\alpha$**:** Conditions include: *Assessment documented as positive using a standardized tool with a follow-up plan; assessment documented as positive, no follow-up plan, and facility has documentation that the patient is not eligible; assessment documented as positive, no follow-up plan, and no reason is given; assessment documented as negative, no follow-up plan required; No documentation of assessment, facility has documentation that the patient is not eligible; No documentation of assessment, no reason given.* | |

Notes: This table presents definitions for reporting metrics used in the Quality Incentive Program score. The conditions listed under Staff Flu Vaccination include multiple scenarios in which the facility reports pain assessment or depression screening documentation for each qualifying patient.

## A.2 Calculating Quality Scores

Quality scores are generated using a set of measures that capture dialysis center performance. The measures are announced a few years prior to their inclusion into the score. Each measure has an individual component score calculated, weighted, and summed to arrive at the domain score, which are again weighted and summed. For each measure, CMS calculates an "achievement" and an "improvement" score. The achievement score relates how a dialysis center performed in year *t-2* relative to a national benchmark two years prior (*t-4*). The improvement score relates how a dialysis center performed relative to its own performance one year prior (*t-3*). The formulas for calculating an individual component score are:

$$\text{Achievement Score} = 9 \cdot \left( \frac{\text{Performance} - \text{Achievement}}{\text{Benchmark} - \text{Achievement}} \right) + 0.5$$

$$\text{Improvement Score} = 10 \cdot \left( \frac{\text{Performance} - \text{Improvement}}{\text{Benchmark} - \text{Improvement}} \right) - 0.5$$

where *Performance* is the performance on the individual metric, *Achievement* is the 15th percentile of national performance, *Improvement* is the center's own previous performance, and *Benchmark* is the 85th percentile of national performance. The scores are then rounded to the nearest integer. Centers that are compared to the national 15th percentile can receive a maximum score out of 10, but centers compared to their own performance can only receive a maximum score of 9. The dialysis center is then assigned the higher of the two scores for that category. The payment penalty threshold is calculated by finding the achievement scores a dialysis center would receive if *Performance* was at the 50th percentile for every metric.

## A.3 Alternative Specifications

### A.3.1 Non-Linear Model

The primary specification in this paper is the linear probability model with year fixed-effects. I show that the estimation from Equation 1.7 is robust to using a logit model, which stems from the assumption that the error term follows a logistic distribution. Table A.3 shows the results from a logistic regression otherwise identical to Table 1.6. Results are transformed to represent the odds-ratio by taking $e^{\beta}$.

Table A.3 Published Quality Scores and Switching, Odds Ratios
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health | (5) Facility Quality | (6) All |
|---|---|---|---|---|---|---|
| **Quality** | | | | | | |
| QIP Score | 0.995*** | 0.995*** | 0.995*** | 0.996*** | 0.997*** | 0.997*** |
| | (0.0007) | (0.0007) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Risk Adjusted Adequate Ratio | | | | | 0.661*** | 0.738*** |
| | | | | | (0.0379) | (0.0437) |
| Risk Adjusted Infection Ratio | | | | | 1.081*** | 1.069*** |
| | | | | | (0.0183) | (0.0184) |
| **Effort Proxy** | | | | | | |
| Effort: Stations | | 0.934*** | 0.956** | 0.956** | 0.957** | 0.957** |
| | | (0.0116) | (0.0180) | (0.0180) | (0.0179) | (0.0181) |
| Effort: High Skill Staff | | 0.904*** | 0.951*** | 0.951*** | 0.953*** | 0.953*** |
| | | (0.0118) | (0.0140) | (0.0142) | (0.0143) | (0.0144) |
| Effort: FTE Staff | | 0.936*** | 0.932*** | 0.934*** | 0.936*** | 0.937*** |
| | | (0.0120) | (0.0133) | (0.0135) | (0.0134) | (0.0135) |
| **Patient Health Characteristics** | | | | | | |
| Dialysis Adequacy | | | | 0.663*** | | 0.699*** |
| | | | | (0.0150) | | (0.0176) |
| Infection Rate | | | | 1.075*** | | 1.067*** |
| | | | | (0.0067) | | (0.0069) |
| Log(Distance) | | 1.414*** | 1.409*** | 1.405*** | 1.406*** | 1.404*** |
| | | (0.0120) | (0.0119) | (0.0117) | (0.0118) | (0.0117) |
| Mean Dep. Var | 6.374% | 6.374% | 6.374% | 6.374% | 6.374% | 6.374% |
| Year FE: | Y | Y | Y | Y | Y | Y |
| Effort: | N | Y | Y | Y | Y | Y |
| Patient Characteristics: | N | N | Y | Y | Y | Y |
| Patient Health: | N | N | N | Y | N | Y |
| Facility Quality: | N | N | N | N | Y | Y |
| Observations | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 | 1,897,315 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: Logit estimation of the effect of published quality scores on the probability of switching. Coefficients are presented as odds-ratios. Column 1 only uses published scores; column 2 adds dialysis center effort and the log of distance; column 3 adds patient and dialysis center characteristics; column 4 includes patients health characteristics but no center quality measures; column 5 includes dialysis center quality measures but no patient health characteristics; column 6 includes both patient health characteristics and dialysis center quality measures. Standard errors are derived using the two-step bootstrap procedure. Select coefficients are excluded for brevity.

Column 1 only includes the quality scores and year fixed-effects. Column 2 adds effort proxy variables for the dialysis centers as well as the log of distance traveled by the patient. Column 3 adds patient and provider characteristics. Column 4 only adds patient health characteristics, whereas column 5 only adds facility quality. Column 6 includes all control variables and showcases the main result. The direction of the effects of the control variables is as expected. For example, an

increase in the QIP score and a higher dialysis adequacy risk ratio are associated with lower odds of switching. A longer travel distance is associated with higher odds of switching. The odds-ratio for the QIP score in column 6 is 0.997, indicating that patients at a dialysis center with a quality score one point higher have a 0.003 lower odds of switching than patients at lower scoring facilities.

I compare the marginal effects for the LPM in Table 1.7 and the logit model in Table A.4. Compared to the LPM, the logit model gives slightly smaller marginal effects. In column 1, the difference between the score elasticity is about 0.05 points. This increases slightly to 0.102 points in column 6. The effects at the $10^{th}$ and $90^{th}$ percentiles are also similar between the two models. In column 1, the LPM predicts a switching likelihood of 7.35% at the $10^{th}$ percentile and 5.54% at the $90^{th}$ percentile, for a percentage point difference of 1.81 and a percent difference of 28.11. The logistic model, on the other hand, predicts a 7.39% and 5.60% likelihood of switching, respectively, for a percentage point difference of 1.8 and a percent difference of 27.73. The relationship is similar in column 6, where the LPM predicts a 6.41% and 5.31% likelihood of switching at the 10th and 90th percentiles, respectively, a percentage point difference of 1.1 and percent difference of 18.91. The logistic model predicts a 6.27% and 5.23% likelihood of switching at the $10^{th}$ and $90^{th}$ percentiles, respectively, a percentage point difference of 1.1 and percent difference of 18.04. The similar marginal effects for both models lends evidence to the notion that the LPM captures most of the effects of quality scores.

Table A.4 Elasticity and Marginal Effects of Published Quality
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health Only | (5) Facility Quality Only | (6) All |
|---|---|---|---|---|---|---|
| QIP Elasticity (LPM) | -3.013 | -3.315 | -2.990 | -2.721 | -2.060 | -2.020 |
| *(10%/% change)* | (0.4041) | (0.3977) | (0.3759) | (0.3682) | (0.3579) | (0.3562) |
| **QIP Elasticity (Logit)** | -2.959 | -3.073 | -2.782 | -2.528 | -1.962 | -1.918 |
| *(10%/% change)* | (0.0430) | (0.3857) | (0.3628) | (0.03555) | (0.3393) | (0.3386) |
| 10th Percentile (LPM) | 7.3566 | 6.8543 | 6.7044 | 6.6300 | 6.4262 | 6.4191 |
| **10th Percentile (Logit)** | 7.3975 | 6.8582 | 6.5762 | 6.4811 | 6.2966 | 6.2759 |
| 90th Percentile (LPM) | 5.5437 | 5.0206 | 5.0632 | 5.1350 | 5.2956 | 5.3099 |
| **90th Percentile (Logit)** | 5.5961 | 5.1327 | 5.0583 | 5.1060 | 5.2322 | 5.2369 |
| Difference (LPM) (pp) | 1.813 | 1.834 | 1.641 | 1.495 | 1.131 | 1.109 |
| Difference (LPM) (%) | 28.11 | 30.88 | 27.89 | 25.41 | 19.29 | 18.91 |
| **Difference (Logit) (pp)** | 1.801 | 1.726 | 1.518 | 1.375 | 1.064 | 1.1039 |
| **Difference (Logit) (%)** | 27.73 | 28.78 | 26.09 | 23.73 | 18.46 | 18.04 |

Notes: This table compares the elasticity and marginal effects of published quality scores between the LPM and logit model, using data from 2012-2019. Each column corresponds to the same column in Table 1.6 and A.3. All estimations include other quality measures, effort proxy variables, provider characteristics and patient attributes, and year fixed-effects. Elasticity is scaled to show the % change due to a 10% increase in the quality score. All coefficients are statistically significant at the 1% level. Standard errors are derived using the two-step bootstrapping procedure with 250 replications.

### A.3.2 Unobserved Heterogeneity

The estimation from Section 5 may suffer from unobserved heterogeneity at the patient or provider level. If this is the case, then the estimates will be biased and incorrectly attribute the effects of idiosyncracies to quality scores. For example, a dialysis center may have exemplary amenities, such as new televisions and state-of-the-art chairs for treatment. Patients at this dialysis center may have lower rates of switching, regardless of the actual quality score. As another example, a dialysis center may have patients that are fiercely loyal to the floor manager or other staff members because of high levels of competence or excellent customer service.

I account for possible unobserved heterogeneity by including various fixed-effects, including dialysis center, patient, and market (HSA). I re-estimate the effect of published quality on switching

from Table 1.6 (Column 6, Row 1) and present these results in Table A.5. Column 1 shows the estimation with only year fixed-effects, which is copied from Table 1.6. Column 2 adds only patient fixed-effects, Column 3 adds only dialysis center fixed-effects, and Column 4 adds only market fixed-effects. Column 5 includes both patient and provider fixed-effects.

Table A.5 Unobserved Heterogeneity
Data from 2012-2019

| Pr(Switch=1) | (1) Baselevel | (2) Patient | (3) Provider | (4) Market | (5) Patient/Provider |
|---|---|---|---|---|---|
| QIP Score | -0.020*** | -0.004 | -0.007** | -0.021*** | -0.005 |
| | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) |
| Observations | 1,897,316 | 1,791,460 | 1,897,299 | 1,897,305 | 1,791,442 |
| R-squared | 0.028 | 0.307 | 0.040 | 0.033 | 0.337 |
| Year FE | **YES** | **YES** | **YES** | **YES** | **YES** |
| Patient FE | NO | **YES** | NO | NO | **YES** |
| Provider FE | NO | NO | **YES** | NO | **YES** |
| Market FE | NO | NO | NO | **YES** | NO |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table repeats the estimation from Column 6 of Table 1.6 but with various fixed-effects. Column 1 is the base-level estimation and only includes year fixed-effects. Columns 2 and 3 include only patient or provider fixed-effects, respectively. Column 4 includes HSA (market level) fixed-effects. Column 5 includes year, patient, ad provider fixed-effects. All specification include patient and provider characteristics, as well as alternative measures of quality.

The inclusion of fixed-effects affects the magnitude of the estimations. Patient fixed-effects shifts the results toward zero, suggesting that the model does not capture much within patient variation. When including provider fixed-effects, the coefficient is -0.007, suggesting that when a dialysis center has their score increase by one point, the likelihood of a patient switching decreases by 0.007 percentage points.

## A.4 Historic Quality Scores

Quality scores in the current time period are the most likely source of quality information, but patients could be using the trend of quality scores to make their decision to switch. For example, patients might be more responsive to consecutive years of low quality than a single year of low quality. However, this response is likely small. Recall from Figure 1.1 that the only score shown is the current year's score. Historic quality scores are not shown, and patients must navigate the CMS website to observe the quality scores in previous years.

I provide support for historic scores having a small effect by estimating the same specification from Table 1.6 but including the current score and the score from the previous year. I show the point estimates in Table A.6 and the 10% elasticity of both the current score and lagged score in Table A.7. The effect of the lagged score is between 1/4 and 1/3 of the effect of the current score. In column six of Table A.6, which controls for all patient and dialysis center covariates, an increase in the lagged quality score by one point decreases the likelihood of switching by 0.006 percentage points, but the effect of the current quality score is 0.019, which is identical to the earlier estimation in Table 1.6.

Table A.6 Current and Lagged Published Quality Score
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health Only | (5) Facility Quality Only | (6) All |
|---|---|---|---|---|---|---|
| Lagged QIP Score | -0.008** | -0.009*** | -0.009*** | -0.008** | -0.006* | -0.006* |
| | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| QIP Score | -0.031*** | -0.032*** | -0.028*** | -0.025*** | -0.019*** | -0.019*** |
| | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Standard errors clustered at the dialysis center level | | | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | | |

Notes: Estimation of the effect of the current quality score and the quality score from the prior year on the likelihood of switching. The estimations are identical to Table 1.6 but with the inclusion of the lagged quality score. Standard errors are clustered at the dialysis center level

The estimate of the elasticity shows a similar pattern, as shown in Table A.7. The lagged quality score has an effect between 1/4 and 1/3 of the current quality score. In the last column, a 10% increase in the prior quality score decreases the likelihood of switching by 0.586%, but a 10%

increase in the current quality score decreases the likelihood of switching by 2.108%.

Table A.7 Elasticity of Current and Lagged Published Quality Score
Data from 2012-2019

| Pr(Switch=1) | (1) No Controls | (2) Effort/Distance | (3) Characteristics | (4) Patient Health Only | (5) Facility Quality Only | (6) All |
|---|---|---|---|---|---|---|
| Lagged QIP Score (10%), | -0.749** | -0.967*** | -0.928*** | -0.832** | -0.600* | -0.587* |
| | (0.331) | (0.354) | (0.348) | (0.346) | (0.343) | (0.342) |
| QIP Score (10%) | -3.175*** | -3.519*** | -3.178*** | -2.818*** | -2.180*** | -2.108*** |
| | (0.460) | (0.469) | (0.455) | (0.449) | (0.442) | (0.441) |
| Standard errors clustered at the dialysis center level | | | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | | |

Notes: Elasticity of the current and lagged published quality score. Estimates are evaluated at the mean value for all covariates. Standard errors are clustered at the dialysis center level.

## A.5 Static or Dynamic Quality

One of the primary assumptions used is that quality is static: a low scoring dialysis center today was a low scoring dialysis center yesterday. The static quality assumption is necessary to determine whether patients are at a high or low quality center before scores are available. Using variable measures of quality, such as the predicted quality scores and the risk-adjusted ratios, produces estimates that are larger than the static measures. A more informative comparison, however, is between the quartiles of these quality measures, which helps account for the influence of outlier values. I show these results in Table A.8. The first column uses the quartiles of the average quality score from 2018-2019 Table 1.9. The second column recreates the estimates from Table 1.11. The last column uses the quartiles of the dialysis adequacy risk ratio. The quartiles of the average quality score have a larger effect and greater statistical significance than the predicted quality score, and are somewhat larger than the dialysis adequacy risk ratio. The dialysis adequacy risk ratio quartiles have a decreasing effect at higher levels after 2013. Using dynamic quality measures provides a complementary look at the effect of quality on switching, although the static measures remain my preferred specification.

Table A.8 Quartiles of Quality and Switching

| Pr(Switch=1) | (1) Average 2018-2019 Quartile | (2) Predicted QIP Quartile | (3) Dialysis Adequacy RR Quartile |
|---|---|---|---|
| **Quality** | | | |
| (Quartile 2)*Post | -0.5759*** | -0.0126 | -0.5747*** |
| | (0.1528) | (0.1438) | (0.1527) |
| (Quartile 3)*Post | -0.6213*** | -0.1783 | -0.5123*** |
| | (0.1407) | (0.1492) | (0.1546) |
| (Quartile 4)*Post | -0.7418*** | -0.2683* | -0.5061*** |
| | (0.1399) | (0.1510) | (0.1500) |
| Post | 1.3159*** | 0.9324*** | 1.2591*** |
| | (0.1763) | (0.1768) | (0.1883) |
| Quartile = 2 | 0.2383* | -0.1245 | 0.0631 |
| | (0.1273) | (0.1097) | (0.1104) |
| Quartile = 3 | 0.0691 | 0.0455 | -0.0410 |
| | (0.0118) | (0.1234) | (0.1129) |
| Quartile = 4 | 0.0865 | 0.0363 | -0.0914 |
| | (0.1764) | (0.1394) | (0.1116) |
| Observations | 3,019,498 | 3,033,210 | 3,033,210 |

Bootstrapped standard errors with 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimated effect of quality on switching using the quartile of average quality from 2018-2019 in the first column; the quartile of the predicted quality score in the second column; and the quartile of the dialysis adequacy risk ratio in the third column. All estimations include patient and provider characteristics from column 6 of Table 1.9. The *Post* variable is an indicator for the years after 2013. Standard errors are estimated using the bootstrap procedure.

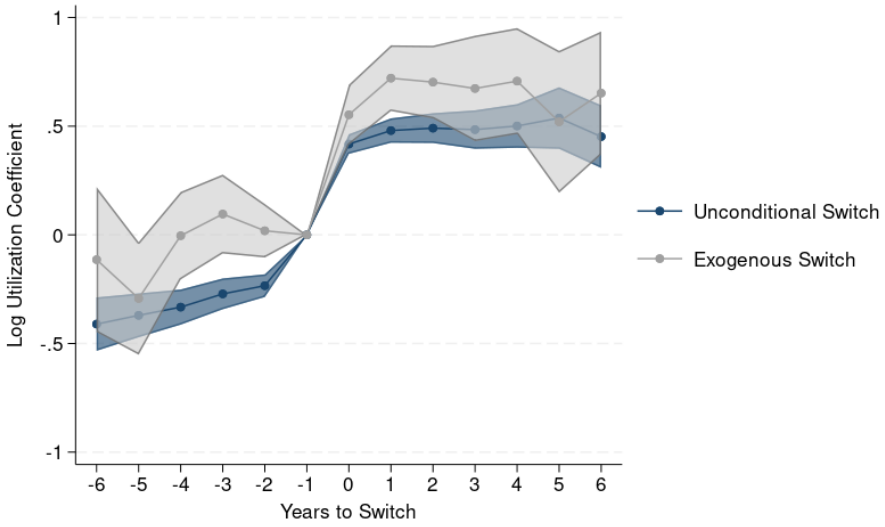
# APPENDIX B

# APPENDIX TO CHAPTER 2

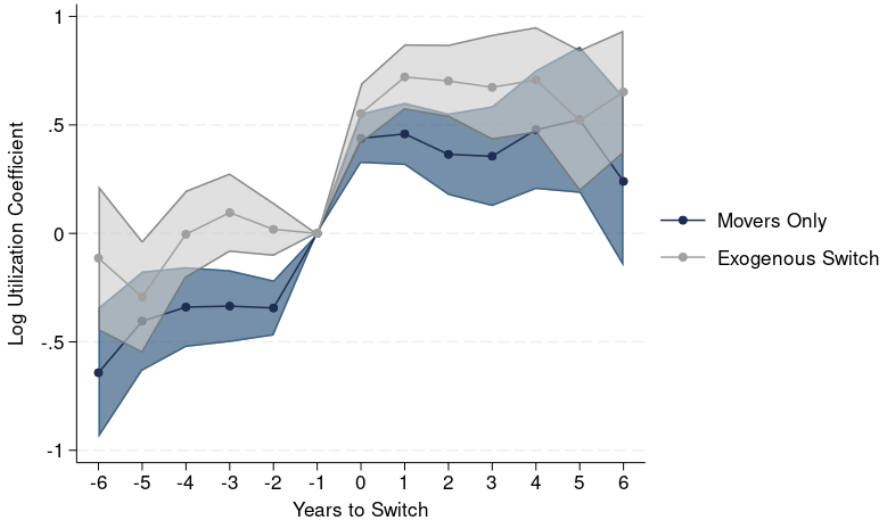
## B.1 Sample Restrictions

The primary sample considers patients that switch because of an acquisition, a closure, or a new competitor opening nearby. Patients that switch due other reasons, such as a move or because of dialysis center quality, are omitted. In this section, I repeat the primary event study estimation and include additional switchers. There are 134,368 unconditional switchers and 16,834 switchers due to a move. I focus on the log of total spending for clarity; the interpretation is similar when looking at other utilization variables.

The results are shown in Figure B.1. Panel B.1a compares all switchers to those considered in the previous sections, which I label as "exogenous switchers", and Panel B.1b compares those that switch due to a move to exogenous switchers. In both estimations, the coefficients for the new groups exhibit pre-trends in the years leading up to a switch and then level off in the years after. One possible explanation is that these patients are switching for reasons related to their health. For example, they could have received a costly diagnosis and moved closer to family, and changed dialysis center in the process.




(a) All Switchers and Exogenous Switchers




(b) Switches from Moves and Exogenous Switchers

Figure B.1 Event Study Estimates with All Switcher and Movers
Notes: Event study estimations from equation 2.4. Exogenous switchers used in the priumary specification are shown in light-grey. The top panel (a) compares exogenous switchers to all switchers, regardless of reason. The botton panel (b) compares exogenous switchers to those that switch due to a move. Standard errors are clustered at the dialysis center level.

## B.2 Heterogeneous Response

In this section, I explore whether patients across several dimensions are responding differently to the change in utilization environment. The outcome of interest and corresponding $\Delta_i$ are the log of total non-dialysis spending. I re-estimate the static difference-in-differences specification on different subgroups of my sample, and show the results in Table B.1. The first two columns show the $\beta$ coefficient and robust standard errors for the $\Delta_i \times Post$ interaction term without controlling for whether a patient is hospitalized. The last two columns include a binary variable for whether a patient is hospitalized in a given year.

Table B.1 Heterogeneous Response

| | Without Hospitalizations | | With Hospitalizations | |
|---|---|---|---|---|
| | $\beta$ | *Std. Error* | $\beta$ | *Std. Error* |
| Male | 0.701 | *0.074* | 0.452 | *0.071* |
| Female | 0.492 | *0.055* | 0.254 | *0.045* |
| White | 0.624 | *0.060* | 0.371 | *0.053* |
| Non-White | 0.608 | *0.074* | 0.371 | *0.070* |
| Black | 0.620 | *0.093* | 0.392 | *0.090* |
| Non-Black | 0.614 | *0.056* | 0.362 | *0.050* |
| Hispanic | 0.449 | *0.117* | 0.293 | *0.102* |
| Non-Hispanic | 0.636 | *0.055* | 0.384 | *0.052* |
| Under 65 | 0.415 | *0.065* | 0.181 | *0.054* |
| Over 65 | 0.798 | *0.071* | 0.537 | *0.070* |
| Medicaid | 0.530 | *0.061* | 0.272 | *0.048* |
| No Medicaid | 0.653 | *0.066* | 0.414 | *0.062* |
| Nephrologist | 0.553 | *0.066* | 0.335 | *0.056* |
| No Nephrologist | 0.540 | *0.097* | 0.345 | *0.082* |
| On Kidney Transplant Waitlist | 0.420 | *0.104* | 0.245 | *0.082* |
| Not On Kidney Transplant Waitlist | 0.651 | *0.054* | 0.395 | *0.051* |
| Urban | 0.620 | *0.060* | 0.387 | *0.057* |
| Rural | 0.600 | *0.091* | 0.319 | *0.080* |
| Above Average Pre-switch Spending | 0.539 | *0.061* | 0.401 | *0.039* |
| Below Average Pre-Switch Spending | 0.679 | *0.064* | 0.392 | *0.061* |
| Positive Delta | 0.497 | *0.075* | 0.268 | *0.064* |
| Negative Delta | 0.986 | *0.134* | 0.747 | *0.128* |

Notes: This table shows the results from estimating the static difference-in-differences specification along several patient dimensions. I show the coefficient on$\Delta_i * Post$ and the corresponding standard errors. The first two columns do not control for whether a patient is hospitalized in a given year, whereas the last two columns do control for whether a patient is hospitalized. I include 5-year age bins, calendar year fixed effects, and patient fixed effects. Standard errors are clustered at the dialysis center level. All coefficients are statistically significant at the 1% level.

The first two rows divide the sample into males and females. Across both specifications, males are about 20 basis points more responsive to a change in the utilization environment after a switch, compared to women. The next six columns compare white and non-white; black and non-black; and Hispanic and non-Hispanic patients. A patient's race does not appear to differentially affect the change in utilization. The coefficients within and between the white/non-white and black/non-black groups are similar. For example, when not controlling for whether a patient is hospitalized, dialysis centers explain 62.4% of the variation in spending for white patients and 60.8% for non-white

patients. Dialysis centers explain 62% of the variation in spending for black patients and 61.4% of the variation for non-black patients. The results are lower but similarly distributed when controlling for hospitalizations. For Hispanic patients, dialysis centers explain about 44.9% of the variation, but this increases to 63.6% for non-Hispanic patients.

For patients over the age of 65, dialysis centers account for nearly 80% of the variation in spending, but only 41.5% for those under the age of 65, suggesting that older patients are more susceptible to the influence of their dialysis provider. Dialysis centers explain about 53% of the variation in spending for patients with Medicaid, which increases to 65.3% for those without Medicaid. Whether a patient is under the care of a nephrologist does not affect the estimates, 55.3% compared to 54.0%, but we do observe a differential response based on whether a patient is on the kidney transplant waitlist, 42% compared to 65.1%. The estimates do not change depending on whether a patient is in an urban versus rural area, 62% compared to 60%, but a discrepancy does arise when controlling for hospitalizations: 38.7% to 32%.

Last, I divide the sample into spending above or below the origin dialysis center's average, and whether a patient moves to a relatively higher or lower spending dialysis center. When not controlling for hospitalizations, dialysis centers explain 54% of the variation in spending for patients with spending above the origin average and 68% for those below the origin average. After controlling for hospitalizations, these values drop to 40% and 39.2%, respectively. When not controlling for hospitalizations, higher spending dialysis centers explain about 50% of the variation in spending, but relatively lower spending dialysis centers explain almost all the variation in spending, 98.6%. However, when controlling for hospitalizations, these estimations drop about 25 basis points. Overall, patients are responding differently depending on observable characteristics, suggesting that policies aimed at addressing supply-side factors should take into consideration these characteristics. For example, an effective targeted policy would address discrepancies between Medicaid and non-Medicaid patients, but addressing differences in nephrology care would be less effective.

# APPENDIX C

# APPENDIX TO CHAPTER 3

## C.1 Additional Summary Statistics by Treatment Status

The treatment variable of interest is the assignment of a payment penalty. Table C.1 shows summary statistics for dialysis centers before and after 2012, split between those are penalized and those that are never penalized. Both types of dialysis center progress similarly before and after 2012. For-profit status increases by 2 percentage points, and chain affiliation increases by about 5 percentage points. Penalized dialysis centers have more dialysis stations and higher staff levels, treating about 15 more patients than the non-penalized centers. The share of patients that have Medicare coverage declines for both groups due to increasing prevalence of more generous private insurance coverage. One final note is that penalized dialysis centers have a higher proportion of patients that are black or non-white.

Table C.1 Summary Statistics by Treatment Status Before and After 2012

| | Never Treated | | Treated | |
|---|---|---|---|---|
| | Pre 2012 Mean | Post 2012 Mean | Pre 2012 Mean | Post 2012 Mean |
| **Center Attributes** | | | | |
| Profit Status | 86.00 | 88.73 | 84.80 | 87.08 |
| Chain Affiliation | 86.19 | 90.94 | 80.65 | 85.16 |
| Dialysis Stations | 17.10 | 16.61 | 18.57 | 18.45 |
| Total Staff | 13.77 | 13.77 | 15.07 | 15.26 |
| **Dialysis Types Offered** | | | | |
| Hemodialysis | 96.52 | 96.32 | 97.27 | 97.36 |
| Peritoneal Dialysis | 42.99 | 48.63 | 47.80 | 52.53 |
| Home Dialysis | 18.11 | 26.81 | 19.42 | 28.91 |
| **Patient Characteristics** | | | | |
| Total Patients | 100.68 | 97.69 | 114.14 | 113.22 |
| Medicare | 88.28 | 73.28 | 87.76 | 72.47 |
| Non-Medicare | 3.72 | 25.55 | 3.99 | 26.21 |
| Average Patient Age | 63.73 | 63.85 | 63.30 | 63.44 |
| Female | 45.14 | 43.17 | 45.34 | 43.60 |
| Hispanic | 15.39 | 16.68 | 9.91 | 12.09 |
| Black | 22.16 | 21.42 | 33.67 | 31.58 |
| White | 70.96 | 70.80 | 62.09 | 63.58 |
| Years on Dialysis | 4.19 | 4.72 | 4.28 | 4.85 |
| Patients Employed | 21.61 | 19.62 | 18.92 | 17.39 |
| Patients in School | 3.50 | 1.20 | 2.96 | 1.17 |
| Number of Comorbidities | 3.07 | 3.07 | 3.09 | 3.13 |
| **Nephrologist Care** | | | | |
| No Nephrologist | 29.46 | 20.77 | 30.26 | 22.34 |
| Nephrologist $<$ 6 months | 14.04 | 14.74 | 13.80 | 14.51 |
| Nephrologist 6-12 months | 19.32 | 20.21 | 18.84 | 18.97 |
| Nephrologist $>$ 12 months | 25.68 | 31.74 | 23.93 | 28.85 |
| **Market Concentration** | | | | |
| HHI | 0.49 | 0.41 | 0.43 | 0.36 |
| Competitors | 8.04 | 11.45 | 9.62 | 14.20 |
| Observations | 13002 | 23310 | 19151 | 28451 |

Notes: Summary statistics are shown for dialysis centers, divided into never treated and treated groups, before and after 2012.

For most categories, penalized dialysis centers have worse outcomes than never penalized centers. The percentage of hospitalizations due to sepsis are over 1.5 percentage point higher for penalized centers compared to non-penalized centers before 2012. After 2012, the value increases by 0.19 percentage points for never-penalized centers and decreases by 0.28 percentage points for

those that are eventually penalized. We observe a similar trend for dialysis patient deaths, where never-penalized centers have fewer deaths in both periods, but the difference decreases after 2012.

Table C.2 Outcomes of Interest by Treatment Status Before and After 2012

| | Never Treated | | Treated | |
|---|---|---|---|---|
| | Pre-2012 | Post-2012 | Pre-2012 | Post-2012 |
| % Hospitalizations for sepsis | 10.72 | 10.91 | 12.36 | 12.08 |
| | (5.638) | (5.211) | (5.920) | (5.487) |
| Survival Category | 1.04 | 1.04 | 0.97 | 0.97 |
| | (0.359) | (0.380) | (0.383) | (0.412) |
| Worse than Expected | 0.05 | 0.05 | 0.09 | 0.10 |
| | (0.209) | (0.220) | (0.286) | (0.302) |
| As Expected | 0.87 | 0.85 | 0.85 | 0.83 |
| | (0.337) | (0.353) | (0.355) | (0.376) |
| Better than Expected | 0.08 | 0.10 | 0.06 | 0.07 |
| | (0.278) | (0.294) | (0.233) | (0.253) |
| Dialysis patient deaths | 11.62 | 10.67 | 14.07 | 12.88 |
| | (8.321) | (7.395) | (9.501) | (8.792) |
| Standard Mortality Ratio | 0.98 | 0.97 | 1.06 | 1.04 |
| | (0.368) | (0.366) | (0.388) | (0.386) |
| Standard Readmission Ratio | 0.95 | 0.94 | 1.03 | 1.03 |
| | (0.325) | (0.281) | (0.296) | (0.281) |
| Dialysis Patients Kidney TX | 2.34 | 2.25 | 2.53 | 2.37 |
| | (2.573) | (2.451) | (2.802) | (2.633) |
| Center-Years | 12,434 | 22,629 | 18,516 | 27,976 |

Notes: Outcome variables of interest are shown for dialysis centers. Sample is divided into never treated and treated groups. Statistics are shown for both types before and after 2012.