ENTRY BARRIERS IN PROVIDER MARKETS: EVIDENCE FROM DIALYSIS CERTIFICATE-OF-NEED PROGRAMS

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Abstract. How do entry barriers in provider markets affect market structure and welfare? In the US, certificate-of-need programs prohibit capacity investment when a community's "needs" are met. I examine their effects in the dialysis industry, where patients are sensitive to access and quality. I find that they reduce entry and protect incumbents from potential competition. I use variation from two natural experiments and a structural model of patient preferences to find that marginal entrants improve access and the patient-treatment match, lower congestion, and raise monthly countywide patient welfare by an amount equal to reducing travel by 9,254 miles.

Keywords: entry barriers, certificate-of-need, dialysis, access, congestion, health planning

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1 Introduction

Health care expenditures in the US are high and rising. Concerned that costs were being driven by moral hazard and provider-induced demand, lawmakers in the 1960s-70s established certificate-of-need (CON) programs to regulate health care capacity investment (Salkever 2000; Knuepfer 1974; Arrow 1963; Roemer 1961). Still widely used, they are now among America's oldest health care cost-containment initiatives. In states with CON programs, hospitals, nursing homes, and other providers seeking to open new facilities or expand existing capacity must receive permission from a state health planning agency. The agency may block any investments that it finds are "unnecessary."

I investigate how CON programs affect market structure, treatment access, patient health, and welfare in the US dialysis industry. Early studies compared states with and without CON programs and focused on hospitals. Their results vary, with some suggesting that CON programs are positively, negatively, and not significantly associated with hospital capacity and costs (e.g., Sloan and Steinwald 1980; Hellinger 1976; Salkever and Bice 1976). Recently, studies have begun using new sources of quasi-experimental variation to measure CON programs' effects on cardiac surgery, home health, and MRI technology (e.g., Perry 2017; Polsky et al. 2014; Cutler et al. 2010).

I focus on dialysis for several reasons. First, it is a life-sustaining treatment for end-stage renal disease (ESRD) provided at specialized clinics called dialysis centers. Most individuals with ESRD are over 60 and suffer from other chronic conditions; they accounted for 1% of enrollees but 7.2% of expenditures in fee-for-service (FFS) Medicare in 2018 (USRDS 2020). Their poor health and dependence on nonresidential care may make their welfare and spending sensitive to CON-induced variation in access and quality, if any. Second, while critics of CON programs argue that they dampen competition by "help[ing] incumbent firms amass or defend dominant market positions," there is little empirical evidence of this phenomenon to date (e.g., Ohlhausen 2015). Whether CON programs protect incumbents from potential entrants is especially important in the dialysis industry because it is already highly concentrated (e.g., Wollmann 2024).

I contribute three main findings using novel sources of policy variation. First, I analyze the application process in North Carolina, where the NC dialysis CON program permits potential entrants to file applications for certificates of need when a simple function of public data crosses a published threshold. I combine variation generated by these threshold-crossings with certificate of need application data to show that the NC dialysis CON program reduces entry, protects incumbents from potential competition, and enables incumbents to expand geographically.

Second, I measure how centers on CON programs' policy margins affect access, congestion, and health using data from the U.S. Renal Data System (USRDS). I combine the threshold-crossings in North Carolina with a 2007 reform in Washington that reduced its CON program's entry barriers. I use an instrumental variables difference-in-differences (IV-DID) research design. I focus on counties without existing centers to eliminate concerns about selection driven by incumbent behavior. I find that on average, marginal centers reduce the distance between patients and their chosen centers by 8.670 miles (34% of the mean) and reduce at-home dialysis utilization by 7.6 percentage points. Together, these findings indicate that CON programs reduce access enough to induce some patients to forgo travel (and the help of their center's staff). Marginal centers also lower congestion: on average, they increase the stations-per-patient and nurses-per-patient at patients' chosen centers by 0.105 (46%) and 0.038 (63%), respectively. Finally, I find evidence that marginal centers improve health on average, but the point estimates are not statistically significantly different from zero.

Third, I estimate a structural model of patient preferences to measure the marginal centers' effects on patient welfare. In the model, patients choose between nearby centers and at-home dialysis after considering their travel costs, switching costs, and alternative-specific quality characteristics. Because I do not observe patients make dollar-valued transactions, I measure their expected utility in miles-traveled equivalents (MTEs), which are the utility value of reducing distances to all alternatives by one mile. I combine the structural estimates with the IV-DID design to find that marginal centers increase expected utility by 11 MTEs per patient-month on average (or 359 MTEs per county-month). Since most patients receive dialysis thrice weekly, this is the value of reducing monthly countywide travel by 9,254 miles. Cost report data suggest that marginal centers' reported fixed costs are $43,568 on average per month. A framework for evaluating the marginal centers' benefits and costs suggests that CON programs were blocking welfare-increasing entrants if the dollar value of an MTE is $121 or more, though this threshold is likely an upper bound.

Beyond the literature in health economics about CON programs—which I expand upon below—these findings contribute to two additional strands of literature. First, several studies examine features of health care payment systems designed to contain costs, including deductibles (e.g., Brot-Goldberg et al. 2017), prospective payments (e.g., Grabowski et al. 2011; Meltzer et al. 2002;

Pauly 2000), and bundling (e.g., Eliason et al. 2022; Einav et al. 2022), among others (e.g., Coe and Rosenkranz 2024; Alexander 2020; Ho and Pakes 2014). I contribute an analysis of a prominent policy instrument designed to cut costs by directly capping the supply of health care services.

Second, there is a large literature in industrial organization studying firm entry. Free entry may lead to an excessive or insufficient number of firms depending on the balance of the entrants' externalities. For instance, entrants in markets with differentiated products may impose a negative externality on incumbents by serving consumers that would have been served anyway ("business-stealing") and a positive externality on consumers by making uncompensated improvements to product variety (e.g., Gaynor 2006; Mankiw and Whinston 1986). Several studies have measured the effects of firm entry in a variety of markets (e.g., Gowrisankaran and Krainer 2011; Davis 2006; Rysman 2004; Berry and Waldfogel 1999), but comparatively few have examined the experiences of regulators charged with limiting entry (e.g., Seim and Waldfogel 2013). I contribute to this literature evidence of regulatory entry barriers in the U.S. dialysis industry, where product variety and business-stealing externalities may co-exist because demand is largely inelastic, prices are largely fixed by Medicare, and providers are horizontally differentiated by their locations.

The remainder of this paper proceeds as follows. I describe dialysis, CON programs, and related literature in section 2. I describe the data in section 3. I compare states with and without dialysis CON programs in section 4. I analyze the NC dialysis CON program's application process in section 5. I conduct the IV-DID and welfare analysis in section 6. I conclude in section 7.

2 Background

2.1 Dialysis

Dialysis is the primary treatment for ESRD, a stage of chronic kidney disease characterized by permanent, life-threateningly low kidney function. Healthy kidneys remove waste from blood and contribute to red blood cell production. Without proper care, people with ESRD may become anemic and accumulate metabolic waste, causing them to feel sick within days and die within weeks (NKF 2024a, 2024b). There were up to 131,000 incident cases of ESRD per year in 2000-2019 and there were 565,000 prevalent cases in 2019 (USRDS 2022). ESRD is often caused by diabetes, high blood pressure, glomerulonephritis, and polycystic kidney disease (Mayo Clinic 2024b).

Dialysis treats ESRD by replacing normal healthy kidney function. There are two modalities. The first is hemodialysis (HD). During HD, a patient is intravenously connected to an external machine that filters their blood for 3-5 hours. The second modality is peritoneal dialysis (PD). During PD, dialysis fluid is poured through a catheter into a patient's peritoneal cavity, where it rests for a few hours and filters blood that passes by naturally. HD typically occurs in a dialysis center thrice weekly (in-center HD), but some patients receive home HD (HHD). PD typically occurs in a patient's residence or workplace daily. Regardless of modality, patients rely on a dialysis center for medication, training, monitoring, and supplies, though HHD and PD ("home dialysis," collectively) typically involve less travel and less assistance from medical professionals.[1] In 2019, 87% of people with ESRD used in-center HD, 11% used PD, and 2% used HHD (USRDS 2022).

A kidney transplant is the primary alternative to dialysis. People with ESRD who receive a new kidney have better prognoses and may no longer need dialysis (Mayo Clinic 2024b). For instance, the expected remaining lifetime of people ages 40 to 74 with ESRD in 2019 was 9-28 years with a transplant and 4-10 years otherwise (USRDS 2022). But donor kidneys are scarce: in 2022, there were only 25,550 transplants nationwide (MedPAC 2024). Consequently, most people with ESRD rely on dialysis (and dialysis centers) to survive.

Dialysis centers are the primary care coordinators and treatment settings for people with ESRD. In 2022, there were 7,865 Medicare-certified centers nationwide. They were mostly freestanding (95%) and for-profit (89%), and had an average of 18 stations—units of capacity that produce one HD session at a time (MedPAC 2024). Their staff include social workers, dieticians, and at least one physician, but nurses and technicians provide most hands-on care. Monitoring patients (e.g., for hypotension) and sanitizing stations (e.g., to reduce infection rates) is labor intensive and subject to a quality-quantity trade-off (Grieco and McDevitt 2017). After years of consolidation, two firms—Davita and Fresenius—together owned 76% of centers in 2022 (MedPAC 2024; Wollmann 2024).

Medicare is a significant source of centers' revenues. In 2019, 84% of people with ESRD had FFS Medicare (65%) or Medicare Advantage (MA) plans (19%). Medicare's prominence in this

[1] There are some clinical and cost differences between HD and PD. For instance, PD patients may experience "longer lasting residual kidney function" but must undergo surgery to place the catheter (Mayo Clinic 2024a). Studies suggest that home dialysis is cheaper per-patient in the long term due to lower labor and overhead costs, but its initiation costs can make it costlier in the short term (Ferguson et al. 2021; Klomjit 2021; GAO 2015).

market arises from the fact that all legal US residents with ESRD and a sufficient work history are Medicare-eligible, regardless of their age.[2] Private plans pay more on average but their rates vary considerably (e.g., League et al. 2022; Lin et al. 2022; Trish et al. 2021; Childers et al. 2019).

FFS Medicare pays dialysis centers a flat per-treatment rate that covers virtually all dialysis-related services, medications, equipment, and supplies (CMS 2019). The rate varies with patient characteristics (including age, body mass index, and comorbidities) and center characteristics (including location and facility-wide patient outcomes), includes add-ons for home dialysis training and high-cost outliers, but does not vary with treatment modality (Fed. Reg. 87 (214), 76 (3)). That the rate varies with facility-wide patient outcomes has lead some centers to provide low-scoring patients with additional care, or, in some cases, discharge them (Bertuzzi et al. 2023). Prior to 2011, prescription drugs were separately billable. Their addition to the payment bundle was associated with lower anemia drug (EPO) volume and fewer hospitalizations linked to EPO complications (Eliason et al. 2022; Swaminathan et al. 2012). Prior to 2005, the rate generally did not vary with patient characteristics (Leavitt 2008; MedPAC 2005, 2000). In 2019, it ranged from \$100 to \$1,000 per treatment and totaled \$10.7B—or \$29,000 per person with ESRD (League et al. 2022; USRDS 2022; Fed. Reg. 83 (220)).[3] Beneficiaries pay a 20% coinsurance rate (CMS 2024b).[4]

2.2 Certificate-of-need programs

States began establishing CON programs in the 1960s, when health care costs were rising rapidly. National health expenditures grew from 5% of GDP in 1960 to 6.9% in 1970, an increase of nearly 40% (CMS 2024a). Medicare and Medicaid—which were established in 1965 as retrospective, cost-based payment systems—heightened concerns that providers were "paid [...] in a manner that provided virtually no efficiency incentives" (e.g., Salkever 2000). Policymakers were in "general agreement" that there was a surplus of health care resources whose costs were being borne indirectly by the public.[5] For instance, in Illinois in 1974, State Senator Jack Knuepfer explained that:

[2]Coverage for people who are Medicare-eligible because of ESRD begins 3 months after ESRD onset (the "waiting period"). If they enroll, for the 30 months following the waiting period (the "coordination period"), Medicare is the primary payer if they have no private coverage; otherwise, Medicare is a secondary payer. Medicare is the primary payer after the coordination period (CMS 2023). Until 2021, people with ESRD generally could not enroll in MA, but could remain in their MA plan if they were already enrolled (Morgan and Kirchhoff 2021).

[3]Total FFS Medicare spending for people with ESRD for all services was approximately \$38.8B (USRDS 2022).

[4]This may be covered by a separate Medicaid or a Medigap plan, which I do not observe (MedPAC 2024).

[5]Fed. Reg. 43(60): p. 13046 (March 28, 1978).

> [The] problem is essentially a surplus in hospital facilities. [...] There are presently plans [...] for almost 61 million dollars worth of new hospitals [...] and it is somewhat doubtful if [...] any [are] needed, since the present hospitals are not nearly full[.] [...] In my business, if I over expand [...] I go out of business. That is not what happens to a hospital. [...] [T]hose bills are paid by a third party payer and we care not one iota what those bills amount to. [...] So the problem of hospital economics is [...] the user cares not what it costs and does not and will not fight a cost increase. [Knuepfer 1974]

Policymakers hoped that CON programs would cut costs by directly "controlling construction, controlling the amount of dollars that goes in" (Salkever and Bice 1979; Knuepfer 1974; Roemer 1961).[6] New York established the first CON program in 1964 and other states soon followed. The National Health Planning and Resources Development Act of 1974 (NHPRDA) created a federal mandate for CON programs, and every state but Louisiana had one by the 1980s. States with higher Medicaid spending established them sooner (e.g., Lanning et al. 1991). The NHPRDA was repealed in 1987, but 35 states and Washington D.C. still had a CON program in 2024.[7]

In general, CON programs prohibit capital projects that do not meet a specific "community need." However, they vary in how they determine whether a capital project is subject to review. For instance, depending on the state, they may review projects associated with hospitals, nursing homes, dialysis centers, or other health care institutions; projects associated with specific technologies, such as MRI scanners; or projects whose costs are forecast to exceed some minimum value. CON programs also vary in how they measure community need. For instance, some CON programs use publicly available formulas that combine published surveys of existing health care resources, population censuses, and estimates of per capita utilization rates; while others follow a less transparent process that culminates in a decision by a health planning commissioner.

Efforts by scholars to measure CON programs' effects have been complicated by potentially endogenous variation in their stringency, areas of focus, and designs, and the opacity of some of their decision-making processes.[8] Early studies were largely descriptive and focused on hospitals. Their

[6] Supporters of CON argue that their rents subsidize indigent care (e.g., Campbell and Fournier 1993; Posner 1971).

[7] For a fuller history and summary of CON programs, see e.g. NCSL (2024), AHPA (2016), Koopman and Philpot (2016), Ohlhausen (2015), AHPA (2006), and Blumstein and Sloan (1978). States continue to use Medicaid to justify their CON programs. For instance, Alaska explains that it "has a vested interest in new health care construction projects and equipment purchases because of the [...] money [it] expends for Medicaid" (ADOH 2024).

[8] For instance, Russell (1979) suggested that "sometimes it is possible to get around the review [...] by [...] splitting the project[.]" Eastaugh (1982) "attempt[ed] to improve the [...] precision of the [...] CON [variable]," but found "that variability in programme implementation was high[;]" and Campbell and Fournier (1993) observed that "[r]egulators

results varied considerably, with some suggesting that CON programs were positively, negatively, and not significantly associated with hospital capacity and costs (e.g., Sloan and Steinwald 1980; Hellinger 1976; Salkever and Bice 1976). Recently, studies have used variation generated by CON repeals, need determination formulas, and state boundaries to produce credible estimates of CON programs' effects on surgical quality, MRI scanners, and home health (e.g., Perry 2017; Polsky et al. 2014; Cutler et al. 2010). States with dialysis CON programs have been associated with less dialysis capacity in the 1980s and 2007, but little is known about their casual effects (Dai and Tang 2015; Dai 2014; Ford and Kaserman 1993). I use novel sources of quasi-experimental policy variation and a combination of structural and reduced-form methods to contribute causal estimates of CON programs' effects on treatment access, patient health, and welfare.

In theory, CON programs may also dampen competition by "help[ing] incumbent firms amass or defend dominant market positions" (e.g., Ohlhausen 2015). Policymakers have said that hospitals had "ask[ed] to be put under this regulation," and CON programs were established sooner in states where market concentration may have helped form lobbying coalitions (Wendling and Werner 1980; Knuepfer 1974).[9] Recent studies show that states that review imaging technology purchases have wider disparities between older and newer hospitals' use of MRI, CT, and PET scans in favor of older hospitals, and home health quality is less sensitive to public reporting in CON states (Baker and Stratmann 2021; Wu et al. 2019), but there is little direct empirical evidence showing whether and how CON programs protect incumbents. I combine CON application data with variation generated by minutiae in the NC dialysis CON program's rules to fill this gap.

3 Data

3.1 Data sources

The primary data for this study are from the U.S. Renal Data System 2018 Database (USRDS Database) (USRDS 2018). The USRDS Database contains standard analysis files (SAFs) derived from CMS data, including Medicare claims, the chronic renal disease medical evidence reports,

[...] enjoy much discretion[.]" Other concurrent policy changes further complicated early studies (e.g., Sloan 1981).

[9] Market participants claim that CON programs facilitate anticompetitive conduct, and some have allegedly successfully appealed to CON programs to withhold certificates-of-need from their competitors (DOJ & FTC 2008, 2004).

death notification reports, and facility surveys. It also contains a 100% sample of institutional Medicare claims for Medicare beneficiaries with renal disease. Other vintages of the USRDS Database have been used elsewhere (e.g., Wollmann 2024; Eliason et al. 2022; Eliason et al. 2020).

I use the USRDS database and some ancillary public datasets to create a sample of patient-months spanning 1980-2016. A patient-month is included in the sample if the patient was receiving dialysis in that month. For each patient-month, I observe a rich set of data encompassing their dialysis treatments, demographics, clinical conditions, residences, insurance status, hospitalizations, Medicare spending, and travel to-and-from dialysis centers. I also use the USRDS Database and ancillary data to create a sample of facility-months spanning 1980-2016. A facility-month is included in the sample if it treated at least one patient in that month. For each facility-month, I observe the center's volume, business model, chain affiliation, location, and staffing.[10]

I also use data from the NC dialysis CON program. First, I use data published in semiannual dialysis reports (SDRs) in 1997-2019 that the NC dialysis CON program used to make need determinations. Second, I use contemporaneous records of applications for certificates-of-need. For each application and its associated project, I observe key dates, the applicant's name, the result of the review process, and the project's location, projected cost, and purpose. I use these data to analyze the NC dialysis CON program's need determination and application process.

Finally, I use data from CMS's Healthcare Cost Report Information System (HCRIS) spanning 2011-2016. HCRIS contains records of Medicare-certified institutional providers' annual cost reports. For each center, I observe several annual measures of reported labor, capital, and administrative costs. I use these data to incorporate centers' reported fixed costs in the welfare analysis.

See appendix A for more information about the data and appendix B for descriptive statistics.

4 Cross-sectional variation between CON and non-CON states

I first compare states with and without dialysis CON programs (CON and non-CON states) to contextualize dialysis CON programs and highlight the identification problem that my IV-DID design will overcome. I also follow the literature and compare counties along CON state borders. I focus on 2004-2016, when surveys indicate that AL, AK, HI, IL, ME, MS, NY, NC, VT, WA, DC, and

[10]Volume varies monthly but other facility-level variables vary yearly. Staffing is available starting in 2004.

WV were CON states.[11] Figure 1 plots CON states and their border counties. I also compare WA and NC to other CON states because I use policy variation there in the IV-DID analysis.

Define indices i for units, t for periods, and c for counties. Let $c(i,t)$ be unit i's county in period t and let $\text{CON}(c)$ indicate that county c is in a CON state. I estimate linear regressions of the form:

$$Y_{it} = \beta \text{CON}\big(c(i,t)\big) + \text{FE}_t \times \text{PatPop}_{c(i,t)} + \varepsilon_{it} \tag{1}$$

where Y_{it} is an outcome, $\text{FE}_t \times \text{PatPop}_{c(i,t)}$ is a period fixed effect interacted with the county patient population, and β measures statewide regression-adjusted average outcome differences between CON and non-CON states. I control $\text{PatPop}_{c(i,t)}$ to account for the possibility that differences in some outcomes—such as the number of centers—are attributable to differences in population size.

In the border analysis, further define the index e for counties in CON states adjacent to non-CON states. For each county e, let $C(e)$ be a set consisting of e and its adjacent counties in non-CON states.[12] The index e now also identifies groups of counties on state borders. I construct a sample of (e,i,t)-level observations such that $c(i,t) \in C(e)$ and re-estimate equation (1) using group-specific period fixed effects interacted with the county patient population. In this analysis, β measures regression-adjusted average outcome differences between adjacent counties on CON state borders. I use state-level cluster-robust standard errors because $\text{CON}(\cdot)$ varies by state. This also account for duplicate data arising from counties in multiple groups $C(\cdot)$.

I first discuss patient characteristics and outcomes. Table 1 shows that patients were 61 years old on average, mostly White (66%), and mostly male (57%). Few were employed at the onset of ESRD (10%) and the most common reported cause of ESRD was diabetes (45%). Table 2 shows that on average in a given month, each patient's nearest center was 3.7 miles away, and their chosen center was 10.5 miles away, had 0.25 stations per patient, and had 0.07 nurses per patient. Patients rarely switched centers (2% of patient-months) or received a transplant (10% of patients). Finally, table 3 shows that on average in a given month, most patients were insured by Medicare FFS (70%). Among these patients, I observe the urea reduction ratio (URR). Typically, URR is increasing in

[11] The American Health Planning Association found in 2004, 2005, 2010, 2012, and 2016 that these states had dialysis CON programs in each survey year, except DC in 2005. I disregard DC's 2005 omission because I have found no evidence that it ended and reinstated its program during 2004-2010. I assume that each state's status as a CON or non-CON state was unchanged in the intervening years. I have not found comparable surveys prior to 2004.

[12] For instance, if e is White, IL, then $C(e)$ consists of White, IL, Gibson, IN and Posey, IN.

session duration and should remain above 65% (NKUDIC 2009). On average in a given month, few patients with Medicare FFS had a URR below 65% (8%), but more had a hospital stay (17%). Their average monthly Medicare spending was $5,313. In each table, columns (5)-(7) report regression-adjusted differences between CON and non-CON states or between WA/NC and other CON states. Table 2 suggests that WA and NC had lower quality staffing ratios on average than other CON states. Most other differences are not statistically or economically significant.

Table 4 describes center characteristics. It shows that on average in a given month, centers were mostly for-profit (80%) and owned by Davita or Fresenius (57%). They served 70 patients, operated 0.77 stations per patient, and were located 8.3 miles from a competing center. Since 2011, their total reported costs were $225,000 and their reported costs per patient were $3,375, on average. Columns (5)-(6) suggest that centers in CON states had higher patient volumes and lower average costs than centers elsewhere. Column (7) suggests that centers in WA and NC were more likely to be owned by Davita and less likely to be owned by a small chain than centers in other CON states.

Finally, table 5 describes countywide dialysis capacity. It shows that on average in a given month, most counties had at least one center (55%); they had 2 centers, 35 stations, and 127 resident patients. Columns (2)-(3) show that counties in CON states had 30 more resident patients per month on average, which highlights the importance of including $\text{PatPop}_{c(i,t)}$ in the regression analysis. Columns (5)-(6) show that counties in CON states had fewer centers and stations than counties in non-CON states with a similar number of resident patients. Column (7) shows that counties in WA and NC were more likely to have at least one center than counties in other CON states.

While my findings that counties in CON states have fewer centers and stations is consistent with the idea that dialysis CON programs are binding on capital investment, these findings primarily highlight two core limitations with a cross-sectional analysis in this context. First, statistical inference is complicated by a lack of sharp variation in $\text{CON}(\cdot)$. This limitation arises from the fact that only eleven states and DC had dialysis CON programs in 2004-2016, that these places were concentrated in the Eastern United States, and that this analysis abstracts from policy features that may vary the strenuousness and scope of dialysis CON programs within and between states.

Second, causal inference is complicated by potential confounding from other, unrelated differences between states, including differences in construction costs or baseline patient health. While the border analysis isolates variation between adjacent counties, some confounding may remain.

For instance, counties in CON states had 47 (28%) more resident patients on average than adjacent counties in non-CON states (not shown). Furthermore, other government programs also vary at the state level.[13] That the cross-sectional analysis abstracts from specific policy features complicates efforts to directly tie differences between states to CON programs per se or investigate mechanisms.

5 Evidence from the application process in North Carolina

While the cross-sectional analysis showed that counties in CON states had fewer dialysis-related capital resources than other counties with similar resident patient populations, it is not clear whether this difference is causally attributable to CON. And while critics of CON argue that it dampens competition by "help[ing] incumbent firms," there is comparatively little empirical evidence of this phenomenon (e.g., Ohlhausen 2015). In this section, I combine application data with variation generated by minutiae in how the NC dialysis CON program determines when a new center is needed. I establish a causal link between the NC dialysis CON program and market structure, and I describe how incumbents can use it to all but eliminate competition from potential entrants. I focus on North Carolina because it is uncommonly transparent about the CON process, and its rules feature thresholds that enable a clear presentation of the statutory mechanism and its implications.

The NC dialysis CON program divides North Carolina into planning areas to make need determinations. The planning areas are generally counties and I refer to them as counties hereafter. It uses two threshold rules. First, it computes how many additional stations are needed to serve a 6-month forecast of each county's resident in-center dialysis patient population assuming that each station serves 3.2 patients ("station deficit"). To illustrate, if a county with 9 stations was forecast to have 64 patients, then its station deficit would be $\frac{64}{3.2} - 9 = 11$.[14] Second, the NC dialysis CON program measures each center's patient-to-station ratio and identifies the lowest ratio in each county, if any ("minimum utilization rate"). A new center may open in a county if the county's station deficit is at least 9.5. If the county has existing centers, then its minimum utilization rate must also be at least 3.2. Applications to open new centers can be filed semiannually after each SDR's publication.

In counties with existing centers ("incumbents"), these rules create two mechanisms for incum-

[13]For instance, Medicaid varies by state and table 3 shows that 36% of patients were dual-eligible in an average month. Moreover, all states with a dialysis CON program also had other CON programs in 2016 (AHPA 2016).

[14]The forecast is based on each county's patient population and lagged 5-year growth rate.

bents to block potential entrants. First, incumbents can ensure that their county's station deficit is always less than 9.5 by investing in new stations as their county's resident in-center dialysis patient population grows. This is feasible under the NC dialysis CON program's rules for capacity investment.[15] Second, incumbents may ensure that their county's minimum utilization rate is always less than 3.2 by treating fewer than 3.2 patients-per-station at one of their centers.

There is a clear financial incentive for incumbents to exercise these opportunities to block potential entrants. First, dialysis centers compete on quality—e.g., cleanliness, staff attention, and comfort—in markets where patients can select from several nearby alternatives (e.g., Eliason 2022; Grieco and McDevitt 2017). They may also compete on price among commercial insurance plans. Second, the NC dialysis CON program permits incumbents to spin off existing stations to new locations in the same county—even if doing so would result in the establishment of a new center. Consequently, incumbents can cut quality investment costs, raise prices, and expand geographically by leveraging the NC dialysis CON program to block potential entrants.

But do incumbents exercise these opportunities? Are the thresholds binding? To answer these questions, I use data in the SDRs to compute each North Carolina county's station deficit and minimum utilization rate for all half-years in 1997-2019. I also use the NC dialysis CON program's application data to identify when someone filed an application to open a new center. Filing applications for certificates-of-need is costly. They are sometimes hundreds of pages long, include patient testimonials, data analysis, construction plans, and financial documents, and require an application fee. Filing an application is therefore a strong signal of an applicant's intention to open a new center.

Define the indices c for counties and t for half-years. Let d_{ct} be the station deficit and let u_{ct} be the countywide minimum utilization rate among incumbents (if any). Define $\tilde{d}_{ct} := d_{ct} - 9.5$, $\tilde{u}_{ct} = u_{ct} - 3.2$, and $\tilde{r}_{ct} := \min(\tilde{d}_{ct}, \tilde{u}_{ct})$. Let Y_{ct} indicate that an application to open a new center was filed. I treat $\tilde{d}_{ct}$ and $\tilde{r}_{ct}$ as running variables in regression discontinuity (RD) designs that respectively measure the average jump in Y_{ct} at $\tilde{d}_{ct} = 0$ (in counties without incumbents) and $\tilde{r}_{ct} = 0$ (in counties with incumbents). In both cases, I use a linear fit, mean-squared error optimal bandwidths, and robust confidence intervals (Calonico et al. 2014a; Calonico et al. 2014b).

Table 6 presents the results. Column (1) shows that when counties without incumbents cross

[15] Existing centers can add new stations if they are treating at least 3.2 patients per station and they are projected to need at least one additional station to serve a 6-month forecast of their own in-center dialysis patient population.

$\tilde{d}_{ct} = 0$, application-filing rates increase by 55 percentage points. Figure 2(a) graphically illustrates this result by plotting Y_{ct} as a function of $\tilde{d}_{ct}$. Figure 2(b) plots station deficits in counties without incumbents in 1997. It shows that threshold-crossings consistently predict application-filing dates. Recall that in a county without incumbents, the station deficit exceeds 9.5 when a 6-month forecast of the county's resident in-center dialysis patient population exceeds $9.5 \times 3.2 = 30.4$. There is no clear reason why this threshold would be discontinuously related to filings unless applicants understood that the NC dialysis CON program's rules were binding.[16]

Table 6 column (2) shows that when counties with incumbents exceed the station deficit and minimum utilization rate thresholds, application-filing rates increase by 43 percentage points. Columns (3)-(4) show that this is entirely driven by applications for totally new centers. Figure 3 graphically illustrates these estimates in the joint distribution between $\tilde{d}_{ct}$ and $\tilde{u}_{ct}$. Panel (a) shows that potential entrants file applications in 82% of county-half-years when station deficits and minimum utilization rates exceed their respective thresholds—and, often, just barely. But it also shows that these conditions are met only 0.6% of the time because incumbents generally keep station deficits low. This is consistent with the idea that the NC dialysis CON program's entry limits are binding on potential entrants and the conditions that would statutorily allow them to enter are rarely met. Meanwhile, panel (b) shows that incumbents commonly expand geographically by applying to spin off stations to new locations, including when potential entrants are statutorily prohibited from entering.

6 The causal effect of centers on CON programs' margins

6.1 Natural experiments in North Carolina and Washington

The foregoing section showed that the NC dialysis CON program's threshold rules are binding on applications to open new centers. In this section, I leverage natural experiments in North Carolina and Washington to confirm that entry follows after the NC and WA dialysis CON programs relax entry limits. I also estimate how entrants on their policy margins affect patient welfare.

In North Carolina, I leverage variation generated in counties without incumbents when I observe

[16]A small number of applications were filed before a threshold-crossing occurred. The applicants may have sought exceptions to the NC dialysis CON program's usual requirements. Half of these centers were ultimately not opened. The RD analysis shows that potential entrants believed that approval was more likely when $\tilde{d}_{ct} \geq 0$ than when $\tilde{d}_{ct} < 0$.

their station deficits first exceed 9.5. The timing and circumstances of these threshold-crossings are plausibly exogenous because they depend only on the counties' resident in-center dialysis patient population sizes and growth rates. While counties with incumbents also sometimes experience threshold-crossings, the timing and circumstances of their threshold-crossings are endogenous to the incumbents' behavior and may therefore coincide with other, unobserved market-level shocks.

In Washington, the WA dialysis CON program uses a similar process to determine whether new centers are needed. Like the NC dialysis CON program, it estimates how many stations are needed to serve a forecast of each county's resident in-center dialysis patient population, and it considers whether any incumbents' utilization rates are low. One important difference is that there is no station deficit threshold: a new center can open to meet a county's need for additional stations even if that need is small. Therefore, while centers' incentives are likely to be similar in Washington and North Carolina, I am unable to use variation generated by threshold-crossings in Washington.

Instead, I use variation generated by a 2007 reform. The reform made entry statutorily easier in two ways in counties that did not have incumbents in 2006 (the "target WA counties"). First, before 2007, the WA dialysis CON program estimated station deficits assuming that each station could serve 4.8 patients. The reform reduced this parameter to 3.2 in the target WA counties. Second, the reform enabled the WA dialysis CON program to estimate a target WA county's station deficit using its own population and the populations of adjacent target WA counties. Figure A1 shows that many target WA counties neighbored one another. Collectively, these changes increased station deficits in the target WA counties, thereby enabling potential entrants to open there with more stations, sooner. I discuss further details of the 2007 WA reform and the NC threshold-crossings in appendix C.

Why only these states? First, I exclude AK, HI, ME, VT, and DC because they have small patient populations or unusual geographies. Second, I exclude AL, IL, MS, NY, and WV because I did not find quasi-experimental variation that can be cleanly linked to the USRDS database. For instance, it is difficult to measure a MS resident's exposure to entrants on the MS dialysis CON program's policy margin because it defines a project's planning area to be a 30-mile area around the project's address (e.g., MS DOH 2013). By contrast, the NC and WA dialysis CON programs define planning areas using pre-existing administrative areas, and the NC dialysis CON program's SDRs and the WA dialysis CON program's reform identify when and where regulatory entry barriers were relaxed.

6.2 Identifying the effect of a marginal dialysis center

I leverage variation generated by the foregoing natural experiments using an IV-DID research design. I regard the 2007 WA policy change and the NC threshold-crossings as events that reduce entry costs in the event counties. Each event's comparison counties are other counties in the US without a center before that event. This strategy identifies causal effects under four assumptions:

A1: Exclusion restriction. The events did not affect outcomes except through their effect on entry. This assumption is plausibly satisfied because the events were administrative decisions that statutorily relaxed dialysis centers' entry barriers and had no other obvious economic or health impacts.
A2: Relevance and monotonicity. The events sometimes made entry more likely, and never made it less likely. This assumption is plausibly satisfied because the events statutorily made entry easier for centers with more stations (in WA) or at all (in NC).
A3: First stage mean independence. Post-event entry rates in the event and comparison counties would have been equal but for the events. This assumption would be satisfied if the average net benefits of entry in the event and comparison counties would have moved in parallel but for the events (e.g., if CON programs raised the level of entry costs, but left time trends unchanged).
A4: Reduced form no anticipation and parallel trends. The events did not affect average pre-event outcomes in the event counties, and average outcomes in the event and comparison counties would have moved in parallel but for the events. This assumption is plausibly satisfied in NC, where the events occurred when forecasted patient populations happened to exceed $9.5 \times 3.2 = 30.4$. In WA, it would be violated if the reform was spurred by declining health or welfare in the event counties. I will therefore examine pre-event outcome trends in the event and comparison counties.

Under these assumptions, IV-DID identifies the average treatment effect of a dialysis center that opened in an event county because of the event. This is the complier average treatment effect at the event site (CATE-ES).[17] The first stage compares entry trends in the event and comparison counties before-and-after the events. The reduced form does likewise for outcome trends. Their ratio identifies the CATE-ES (e.g., Duflo 2001). See appendix D for details and a stylized example.

[17]This term combines IV's "complier average treatment effect" with DID's "average treatment effect on the treated." I use "at the event site" instead of "on the treated" because in IV-DID, the event is the instrument, not the treatment.

6.3 Estimating the effect of a marginal dialysis center

I estimate the CATE-ES using two-stage least squares (2SLS). I address concerns about DID estimation with two-way fixed effects using the stacked regression (Gardner et al. 2024, Goodman-Bacon 2021, Cengiz et al. 2019). Define the indexes e for events, i for patients, c for counties, and t for months. Let $c(i,t)$ and $z(i,t)$ identify patient i's county and ZIP code in month t, respectively. I duplicate the patient-month sample described in section 3 once for each event to generate an (event, patient, month)-level dataset. I keep only those observations (e,i,t) such that $c(i,t)$ is an event or comparison county for e and t is within 72 months of e's effective date.[18] That is, for each event, this dataset is a 144-month patient-level repeated cross-section of the event and comparison counties.

Let $D_{eit} := 1[c(i,t) \text{ has a center}]$. Let τ_e be e's effective date and let the instrument for D_{eit} be $Z_{eit} := 1[c(i,t) \text{ is } e\text{'s event county}]1[t \geq \tau_e]$. I estimate 2SLS models of the form:

$$Y_{eit} = \beta D_{eit} + \Gamma_e X_{eit} + \text{FE}_{ez(i,t)} + \text{FE}_{et} \times \text{PatPop}_{ec(i,t)t} + \varepsilon_{eit} \tag{2a}$$

$$D_{eit} = \delta Z_{eit} + \Omega_e X_{eit} + \text{FE}_{ez(i,t)} + \text{FE}_{et} \times \text{PatPop}_{ec(i,t)t} + \eta_{eit} \tag{2b}$$

where Y_{eit} is an outcome, β is the parameter of interest, X_{eit} is a vector of control variables, $\text{FE}_{ez(i,t)}$ is an event-specific ZIP code fixed effect, and $\text{FE}_{et} \times \text{PatPop}_{ec(i,t)t}$ is an event-specific month fixed effect fully interacted with the county's resident patient population.

Finally, let $\mathcal{W} := \{-6, ..., 5\}$ contain annual leads and lags excluding -1. For every $\tau \in \mathcal{W}$, let $Z_{eit\tau} := 1[c(i,t) \text{ is } e\text{'s event county}]1[\lfloor (t-\tau_e)/12 \rfloor = \tau]$. I also estimate models of the form:

$$Y_{eit} = \sum_{\tau \in \mathcal{W}} \alpha_\tau Z_{eit\tau} + \Lambda_e X_{eit} + \text{FE}_{ez(i,t)} + \text{FE}_{et} \times \text{PatPop}_{ec(i,t)t} + \upsilon_{eit} \tag{3}$$

$$D_{eit} = \sum_{\tau \in \mathcal{W}} \delta_\tau Z_{eit\tau} + \Xi_e X_{eit} + \text{FE}_{ez(i,t)} + \text{FE}_{et} \times \text{PatPop}_{ec(i,t)t} + \omega_{eit} \tag{4}$$

where $(\alpha_\tau : \tau \in \mathcal{W})$ and $(\delta_\tau : \tau \in \mathcal{W})$ measure the dynamic effects of Z on Y and D, respectively.

I use county-level clustered standard errors because the events vary by county. This accounts for duplicate data arising from stacking. I also report 95% VtF critical values (Lee et al. 2023).[19]

[18] I assume that each event's effective date was 18 months after the event because it takes time to open a new center. I chose 18 months because that is the earliest that a new center opened in the event counties after one of the events.

[19] The VtF critical values enable conducting weak instrument-robust inference without using an F-statistic threshold.

6.4 IV-DID results

6.4.1 Dialysis CON programs' effects on entry

Figure 4 plots the estimated dynamic first stage effect of the events on entry. It shows that on average in a given month after the events, patients in event counties were 53% more likely to have a center in their county. In North Carolina, this is consistent with my earlier finding that threshold-crossings caused potential entrants to file applications to open new centers. In Washington, I investigate the link between the reform and entry by checking whether the centers that opened in the target WA counties could have opened under the pre-2007 policy. Table A1 suggests that they would have been too big given their counties' patient populations. While smaller centers may have been statutorily permitted, the fixed cost of entry may have been sufficiently high to deter them.

6.4.2 Dialysis CON programs' effects on patients

Table 7 presents the 2SLS estimates and figure 5 presents the dynamic reduced-form estimates.

First, I study dialysis access outcomes. I find that marginal dialysis centers reduce distances between patients' residences and their chosen dialysis center by 8.670 miles (34% of the mean). They also reduce distances between patients' residences and their nearest dialysis center by 10.490 miles (57% of the mean). They reduce the share of patients who use HHD by 2.3 percentage points and the share who use any at-home dialysis by 7.6 percentage points.

While it is not surprising that new centers would reduce distances between patients' residences and their nearest or chosen centers, the magnitudes of the reductions are striking and consistent with letters written to the WA dialysis CON program by patients in support of potential entrants' applications to open new centers.[20] For instance, one petitioner wrote:

> Last Saturday was [my husband's] 3rd dialysis treatment at Sunnyside. It's [...] so far away. [...] Most of our driving is very local. We do not leave town if there is any question of bad weather. I dread this winter. (STRESS) [...] [Each trip] takes about 7 hours in all. (3 times a week) [...] It's Monday and my husband is so dreading the long trip [...] tomorrow and saying he wants to quit and not go back. [Emphasis original]

That the marginal centers reduced at-home dialysis utilization supports the idea that dialysis CON

[20] These letters were shared with me by the WA Department of Health pursuant to a public records request.

programs change patients' treatment choices: they cause some patients who intrinsically prefer in-center dialysis to choose a self-managed, at-home alternative by blocking entry.

Second, I study congestion and health outcomes. I find that marginal centers increase the stations per patient at an average patient's chosen center by 0.105 (46%). They also increase the nurses per patient at an average patient's chosen center by 0.038 (63%). These findings indicate that the marginal centers reduced congestion. But among patients with FFS Medicare as a primary payer, I do not find that marginal centers reduce monthly hospitalization rates or the share of patient-months associated with a URR below 65%, although both point estimates are negative. Other studies similarly found no evidence of a significant association between CON programs and patient health (e.g., Polsky et al. 2014; Ho et al. 2009; DiSesa et al. 2006; Ho 2006; Popescu et al. 2006).

Appendix E reports results for additional outcomes. I do not find that marginal centers reduce mortality rates, increase in-center HD patients' number of monthly HD sessions, or lower spending.

6.5 Sensitivity analysis

I conduct several sensitivity analyses to evaluate my results. See appendix F for details. First, I evaluate whether my estimates are sensitive to the control variables. Since equations (2)-(4) do not include patient fixed effects, my estimates may be sensitive to changes in the composition of the event or comparison counties' patient populations that happens to coincide with the events.[21] I re-estimate equation (2) without patient-level control variables. The results are qualitatively similar.

Second, I evaluate whether my estimates are sensitive to using a nationwide set of comparison counties. I re-estimate equation (2) with alternative comparison counties. For the NC threshold-crossings, I use counties in North Carolina and neighboring states (GA, VA, TN, and SC). For the 2007 WA policy change, I use counties in the Western United States (OR, ID, MT, WY, CA, NV, NM, AZ, UT, and CO). The results are qualitatively similar.

Third, I evaluate whether my estimates are sensitive to pooling WA and NC events. I re-estimate equations (2)-(4) separately for the 2007 WA policy change and the NC threshold-crossings. The results are qualitatively similar—though the sample size for WA is smaller and the first stage is weaker—suggesting that my findings are not driven by pooling the two states' events.

[21]It is not feasible to use patient FEs because many patients do not survive throughout each event's event window.

6.6 Welfare

In section 6.4, I found that centers on the WA and NC dialysis CON programs' margins improved access, reduced congestion, and reduced at-home dialysis utilization. In this section, I measure their total contributions to patient welfare using a structural model of patient preferences. I compare the marginal centers' estimated patient welfare contributions to estimates of their reported fixed costs.

6.6.1 Patient preferences

Define the indexes i for patients, j for alternatives in the set $\mathcal{J}$, and t for time periods in the set $\mathcal{T}$. Assume that each patient's alternatives are in-center dialysis at any dialysis center within 50 miles of their residence, in-center dialysis 50 miles away, or an at-home dialysis outside option.[22] Let u_{ijt} be patient i's utility for being treated at alternative j in period t. Assume that:

$$u_{ijt} = \gamma \text{TrDist}_{ijt} + \lambda_j \text{Stay}_{ijt} + \delta_{jt} + \varepsilon_{ijt} \tag{5}$$

where TrDist_{ijt} is the distance between patient i's residence ZIP code and center j's ZIP code, γ measures disutility for travel, Stay_{ijt} indicates that j was i's chosen alternative in the previous period, λ_j measures switching costs, δ_{jt} is an alternative-period fixed effect absorbing all time-varying alternative characteristics, and ε_{ijt} is an i.i.d. type 1 extreme value taste shock. Under these assumptions, each patient's expected utility in each month given their choice set is:

$$\bar{u}_{it} := \ln\left(\sum_{j \in \mathcal{J}} \exp\left(-\text{TrDist}_{ijt} + \frac{\lambda_j}{-\gamma}\text{Stay}_{ijt} + \frac{\delta_{jt}}{-\gamma}\right)\right) \tag{6}$$

I express expected utility in miles traveled-equivalents (MTEs) by scaling the parameters by $-\gamma$ because I do not observe patients making dollar-valued transactions. A one unit increase in (6) is equal to the welfare gain of reducing travel distances to all alternatives by one mile.

The model enables measuring three kinds of welfare gains associated with new centers. First, it enables measuring gains from reduced travel costs. The parameter $-\gamma$ measures the value of living closer to dialysis centers, including lower fuel costs, opportunity costs of time, and weather-related

[22] I assume that "forgoing dialysis" is not an alternative because it is necessary for survival without a transplant, demand for transplants far exceeds supply, and I do not find evidence that marginal centers reduce mortality rates.

uncertainty. Second, the model enables measuring gains from a better match to in-center or at-home dialysis. The combination of γ, λ_j, and δ_{jt} measure the value of switching from at-home dialysis to in-center dialysis when a new dialysis center opens nearby. Finally, the model enables measuring gains from a change in the mix of dialysis centers. The parameters δ_{jt} measure the value of each alternative relative to at-home dialysis, including the quality of their staff, stations, and amenities.

I estimate the model using a (patient, month, alternative)-level sample, where a patient-month is included in the sample if it appeared in the IV-DID estimation sample. Initially, there are 6 million patient-months (cases) and 4,994 alternatives, implying more than 800,000 elements of $(\lambda_j : j \in \mathcal{J})$ and $(\delta_{jt} : jt \in \mathcal{J} \times \mathcal{T})$. I simplify the computational problem by restricting $\lambda_j = \lambda$ and $\delta_{jt} = \delta_j$ for all j, t. As a result, γ is estimated from the association between conditional choice probabilities (CCPs) and travel distances, λ is estimated from differences between incident and prevalent patients' CCPs, and each δ_j is estimated from the difference between at-home dialysis utilization anywhere and in-center dialysis utilization at center j. I further reduce the computational cost by estimating the model using the event counties and the regional comparison counties described in section 6.5. The final sample consists of 1.4 million cases and 1,312 alternatives.[23]

Figure 6 reports the estimates. Panel (a) shows that $\hat{\gamma}$ is -0.109 and $\hat{\lambda}$ is 5.875, indicating that patients dislike travel and face switching costs. The switching cost estimate is $-\hat{\lambda}/\hat{\gamma} = 53.8$ MTEs, which is high and consistent with my finding that patients switch centers in only 2% of months on average. Panel (b) plots the distribution of estimated MTE-valued alternative-specific fixed effects. It shows that 95% are positive, indicating that patients tend to prefer in-center to at-home dialysis. It also shows that the centers that opened in the event counties had above-median fixed effects, indicating that they were relatively high quality. The mean-squared choice error is 0.29%.[24]

I use the model's estimates to compute $\hat{\hat{u}}_{it}$ using the plug-in analogue of equation (6). I re-estimate equations (2)-(4) using $\hat{\hat{u}}_{it}$ as an outcome. Table 7 and figure 5 report the results. I find that the marginal centers in the event counties produced a 10.560 MTE expected utility gain per resident patient-month on average. I also aggregate $\hat{\hat{u}}_{it}$ to the (county, month)-level and re-estimate equations (2)-(4) with a stacked county-month dataset. Table 8 reports the result. I find that marginal centers in the event counties produced a 359 MTE expected utility gain per county-month on average.

[23] In appendix F, I add TrDist_{ijt}^2 to allow for quadratic preferences over distance. The results are qualitatively similar.

[24] The MSCE is the average squared difference between each case's estimated CCPs and an indicator variable equal to 1 for each case's choice and 0 otherwise. A low MSCE indicates that the estimated model explains the data well.

6.6.2 Dialysis centers' reported fixed costs

I use HCRIS data to measure centers' reported fixed costs during 2011-2016.[25] Since the event windows span 1992-2016, I use the available data to predict reported fixed costs before 2011. I estimate the model $\ln(\text{FixedCosts}_{jt}) = \beta X_{jt} + \varepsilon_{jt}$, where FixedCosts_{jt} is center j's reported fixed cost in month t and X_{jt} is a vector of center characteristics that I observe throughout the sample period, including age, state, chain affiliation, patient volume, and stock of stations.[26] I aggregate the predicted monthly fixed costs to the (county, month)-level and re-estimate equations (2)-(4) with a stacked county-month dataset using the predicted values as an outcome. Table 8 reports the results. It shows that marginal centers increased reported fixed costs by $43,568 per month on average.

6.6.3 Total welfare

The foregoing estimates contribute to a framework for evaluating the trade-off between the marginal centers' benefits for patients and their effect on costs. Since the CATE-ES is the causal effect of marginal dialysis centers in the event counties in the years following the events, I focus on the counterfactual in which the the marginal centers were delayed further.

First, table 8 shows that marginal centers increase expected utility among the residents of their county by 359 MTEs per county-month on average. This estimate reflects factors that influence patients' choices, but it is not clear that patients' choices reflect all relevant factors. For instance, marginal centers may affect health in ways that are difficult for patients to understand (Arrow 1963). While I did not find that marginal centers improve observed health outcomes, they may affect some unobserved health outcomes, or their effects may be too small to detect in this sample. The marginal centers may also benefit patients in other counties who might travel there for care.[27] Thus, 359 MTEs may understate the marginal centers' benefits for patients.

Second, the dollar value of an MTE is unknown. (Recall that it is not identified because I do not observe patients making transactions in dollars.) In-center dialysis patients typically make 6 one-way trips per week and there are 4.3 weeks per month on average, so the dollar value of one

[25] They are the sum of lines 1-4, 6, and 11 of Form CMS-265-11 Worksheet A, and include "expenses pertaining to buildings and fixtures such as depreciation, insurance interest, [and] rent," "expenses incurred in the operation and maintenance of the plant," and costs of "fiscal services, legal services, accounting, [and] recordkeeping," among others.

[26] Table A2 reports the estimates of β. It shows that there is a positive and concave association between reported fixed costs, volume, and stations. There is also heterogeneity by state, chain, and age (not shown).

[27] On average in a given month, 25% of patients treated at centers in the event counties lived in a non-event county.

MTE may be equal to the dollar value of reducing monthly travel by 25.8 miles. Correspondingly, the dollar value of 359 MTEs may be equal to the dollar value of reducing monthly travel by 9,254 miles. The cost of travel may be low for patients who are relatively healthy, independent, and have a low opportunity cost of time, but it may be high for others, such as those who need a friend or relative to drive, or who cannot sit comfortably on long trips. Estimates of the resource cost of travel—such as gasoline and automobile wear—range from $0.52-1.32 per mile.[28] Using back-of-the-envelope calculations and assumptions about the minimum wage, taxi services, and carpooling rates, Eliason (2022) estimated that dialysis patients' average travel costs are $1.86 per mile.

Third, the marginal centers' effect on total costs is their fixed costs plus their effect on total variable costs. To illustrate, assume that other centers would have treated the marginal centers' patients had the marginal centers not opened, and refer to the marginal centers' patients as switchers and the other centers as incumbents. The marginal centers' effect on total variable costs is the difference between their cost of treating switchers and the incumbents' cost of treating switchers. Studies suggest that dialysis centers' variable costs are a convex function of volume because congestion raises the cost of treating marginal patients (e.g., Eliason 2022). Consequently, it is likely that the marginal centers lowered total variable costs by spreading patients across more facilities.

As for fixed costs, relative to the counterfactual that the marginal centers would have opened later, the only relevant fixed cost is the everyday cost of "keeping the lights on." Table 8 shows that the marginal centers' estimated reported fixed costs were $43,568 per month on average. Recall that this estimate is based on accounting cost data reported by dialysis centers to CMS through HCRIS. Studies suggest that some providers overstate their costs in these reports in part because they are used in aggregate by public payers to set prices (e.g., Gandhi and Olenski 2024). They may also indirectly include some variable costs, such as variable billing and recordkeeping costs.

In sum, I find that CON programs worsen treatment access, patients' matches with their desired treatment modalities, and congestion, through their direct effect on entry. I find that the marginal centers raise total welfare if the dollar value of 359 MTEs per month on average exceeds $43,568; i.e., if the dollar value of an MTE is $121 or more. This threshold is likely an upper bound, because 359 MTEs may understate their benefits for patients and $43,568 may overstate their effect on costs.

[28] This is equal to $0.37-$0.93 per driving mile (AAA 2010) times 1.417 driving miles per straight-line mile (Boscoe et al. 2012). All distances reported in this paper are straight-line miles between ZCTA centroids.

7 Conclusion

In this paper, I study how dialysis CON programs affect market structure, treatment access, patient health, and welfare. I use novel sources of policy variation and a combination of structural and reduced-form methods to make three findings. First, I find evidence that CON programs reduce entry, protect incumbents from potential competition, and enable incumbents to expand. Second, I find that new dialysis centers on CON programs' policy margins improve access and the patient-treatment match, and reduce congestion. I also find evidence that they improve health, but these estimates are not statistically significant. Third, I find that marginal centers raise monthly county-wide patient welfare by the utility value of reducing travel by 9,254 miles. These findings are relevant to ongoing policy discussions about health system capacity, demand fluctuations, and CON reform post-COVID—including in West Virginia, Tennessee, and South Carolina (e.g., Rice 2024; Friedman 2024; SC Governor's Office 2023; Hoe 2022; Bernstein et al. 2020; Abelson 2020).

However, further research is needed. First, that CON programs protect incumbents from potential competition may cause providers to expand faster to become the incumbents being protected instead of the potential entrants being blocked. This CON-induced preemption may improve access and raise costs along some margins. Second, CON programs may influence market structure not only through their effect on entry, but also through their effect on mergers, acquisitions, and firm turnover rates (e.g., Wollmann 2024). They may thereby delay the expansion of new, for-profit or private equity business models (e.g., Gupta et al. 2023; Eliason et al. 2020). Finally, although this paper shows that CON programs protect incumbents from potential competition, their effects on dialysis centers' prices and quality are unknown. Additional research in these areas may be fruitful.

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	Means				Regression-adjusted mean differences		
		CON?			CON vs. no CON		WA/NC vs. other CON
	Overall (1)	No (2)	Yes (3)	WA/NC (4)	Statewide (5)	At borders (6)	Statewide (7)
Age, race, ethnicity, and sex							
Age[1]	61.35	61.36	61.34	60.19	-0.00	0.01	-1.69
White (%)	0.66	0.69	0.58	0.58	-0.10**	-0.00	-0.06
Black (%)	0.28	0.26	0.35	0.37	0.09	-0.00	0.07
AIAN (%)	0.01	0.01	0.01	0.01	-0.01	0.01	0.01***
Asian (%)	0.04	0.03	0.04	0.03	0.01	-0.01	-0.01
NHPI (%)	0.01	0.01	0.01	0.01	0.01	-0.00	-0.01
Hispanic (%)	0.13	0.15	0.08	0.04	-0.06	-0.00	-0.02
Not Hispanic (%)	0.86	0.85	0.92	0.95	0.06	0.00	0.02
Female (%)	0.43	0.43	0.44	0.44	0.01	0.00	0.00
Male (%)	0.57	0.57	0.56	0.56	-0.01	-0.00	-0.00
Employment status at ESRD onset							
Some empl. (%)	0.10	0.10	0.10	0.11	0.00	-0.01	0.01
No empl. (%)	0.88	0.88	0.88	0.88	-0.00	0.01	-0.00
Height and weight at ESRD onset							
Height (cm)	168	168	168	169	0.06	0.11	0.63*
Weight (kg)	83	83	83	85	0.14	-0.09	1.52
BMI	29	29	29	30	0.04	-0.06	0.32
Primary cause of ESRD							
Diabetes (%)	0.45	0.46	0.44	0.46	-0.01	0.00	0.01
Hypertension (%)	0.29	0.29	0.29	0.25	0.00	-0.01	-0.04
Glomer. (%)	0.08	0.08	0.09	0.11	0.01	0.00	0.02**
Cyst. kidney (%)	0.02	0.02	0.02	0.02	0.00	0.00	0.00
Sample composition							
Patient-months (#M)	62.88	49.32	13.56	3.18	62.88	17.89	13.56
Patients (#M)	1.79	1.43	0.40	0.09	1.79	0.38	0.40

Tab. 1. *Patients' demographic and biographic characteristics (2004-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of patient-level observations. Patients are assigned to states based on their dialysis start dates. In columns (5)-(7), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are computed using state-level cluster-robust standard errors. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 10. Source: author's analysis of the USRDS Database.

[1] Estimated from a (patient, month)-level sample.

	Means				Regression-adjusted mean differences		
		CON?			CON vs. no CON		WA/NC vs. other CON
	Overall (1)	No (2)	Yes (3)	WA/NC (4)	Statewide (5)	At borders (6)	Statewide (7)
Miles to nearest alternatives							
Any alternative	3.73	3.75	3.66	4.15	-0.16	0.24	-0.55
With >med. stats/pats	7.80	7.63	8.43	8.95	0.67	1.37*	-1.73
Alternatives within 100 miles							
Centers (#)	161.11	154.62	184.70	93.92	31.44	-7.45	-83.92
Ind. centers (#)	49.25	44.70	65.81	18.19	21.27	-3.67	-51.11
Chains (#)	5.23	5.27	5.12	3.78	-0.14	-0.18***	-1.31
Owners (#)	54.48	49.96	70.93	21.96	21.13	-3.85	-52.41
Chosen center characteristics							
Distance (mi)	10.47	10.66	9.77	10.96	-0.97	0.02	0.07
Stats/pats (#)	0.25	0.25	0.23	0.25	-0.02	-0.03***	0.02
Nurses/pats (#)	0.07	0.07	0.08	0.06	0.00	-0.00	-0.03**
PCTs/pats (#)	0.08	0.08	0.08	0.09	0.00	0.00	0.02***
Diets/pats (#)	0.01	0.01	0.01	0.01	-0.00	-0.00*	-0.00***
Not switched (%)	0.98	0.98	0.98	0.98	-0.00	0.00	0.00
Switched (%)	0.02	0.02	0.02	0.02	0.00	-0.00	-0.00
Treatment modalities							
In-center HD (%)	0.90	0.90	0.90	0.89	0.00	0.01	-0.01
PD (%)	0.09	0.09	0.08	0.10	-0.01	-0.01	0.01
HHD (%)	0.01	0.01	0.02	0.02	0.01	0.00	0.00
Ever TX (%)[1]	0.10	0.10	0.10	0.11	0.00	-0.01	0.01
Sample composition							
Patient-months (#M)	62.88	49.32	13.56	3.18	62.88	17.89	13.56
Patients (#M)	1.79	1.43	0.40	0.09	1.79	0.38	0.40

Tab. 2. *Patients' treatment choices (2004-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of (patient, month)-level observations. In columns (5)-(7), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are computed using state-level cluster-robust standard errors. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 10. Source: author's analysis of the USRDS Database.

[1] Estimated from a patient-level sample. Patients are assigned to states based on their dialysis start dates.

	Means				Regression-adjusted mean differences		
		CON?			CON vs. no CON		WA/NC vs. other CON
	Overall	No	Yes	WA/NC	Statewide	At borders	Statewide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Health insurance enrollment and spending							
MCare FFS Prim. (%)	0.70	0.69	0.71	0.77	0.02	-0.00	0.05
HMO (%)	0.11	0.12	0.09	0.08	-0.03	-0.00	-0.02
Any Medicare (%)	0.78	0.78	0.79	0.84	0.01	-0.01	0.05
Dual eligible (%)	0.36	0.37	0.35	0.41	-0.01	0.04	0.07
Medicare spending ($)[1]	5,313	5,320	5,288	4,885	-19.10	-72.68	-325.84
Dialysis sessions							
In-center HD (#)[1]	10.70	10.70	10.71	10.66	0.00	-0.03	-0.04
HHD (#)[1]	0.20	0.18	0.28	0.29	0.09	0.02	0.06
PD (#)[1]	1.49	1.50	1.46	1.66	-0.06	-0.17	0.10
Urea reduction ratio (URR)							
URR <65% (%)[1]	0.08	0.08	0.08	0.07	-0.00	0.00	-0.00
URR 65-75% (%)[1]	0.44	0.44	0.43	0.41	-0.02	-0.00	-0.03
URR >75% (%)[1]	0.47	0.47	0.49	0.51	0.02	0.00	0.03
Hospitalizations and mortality							
Any (%)[1]	0.17	0.17	0.16	0.15	-0.00	0.00*	-0.01*
Circulatory (%)[1]	0.06	0.06	0.06	0.05	-0.00	0.00	-0.01
Kidney and UT (%)[1]	0.02	0.02	0.02	0.02	-0.00	0.00***	-0.00
Infections (%)[1]	0.01	0.01	0.01	0.01	-0.00	0.00	-0.00
Died (%)[1]	0.02	0.02	0.02	0.01	-0.00	0.00	-0.00**
Sample composition							
Patient-months (#M)	62.88	49.32	13.56	3.18	62.88	17.89	13.56
Patients (#M)	1.79	1.43	0.40	0.09	1.79	0.38	0.40

Tab. 3. *Patients' health outcomes and spending (2004-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of (patient, month)-level observations. In columns (5)-(7), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are computed using state-level cluster-robust standard errors. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 10. Source: author's analysis of the USRDS Database.

[1] Sub-sample associated with Medicare FFS as a primary payer.

	Means				Regression-adjusted mean differences		
		CON?			CON vs. no CON		WA/NC vs. other CON
	Overall	No	Yes	WA/NC	Statewide	At borders	Statewide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age and chain affiliation							
Age	16.62	16.32	17.90	16.30	1.60**	2.39	-1.24
Davita (%)	0.28	0.30	0.22	0.31	-0.08**	0.01	0.11**
Fresenius (%)	0.29	0.29	0.32	0.39	0.04	-0.05	0.09
Small chain (%)	0.15	0.15	0.11	0.06	-0.04**	-0.01	-0.07***
Independent (%)	0.28	0.26	0.35	0.24	0.08	0.05	-0.13
Profit status and hospital affiliation							
For-profit (%)	0.80	0.81	0.74	0.74	-0.07	-0.04	0.00
Not for-profit (%)	0.20	0.19	0.26	0.26	0.07	0.04	-0.00
Freestanding (%)	0.87	0.88	0.83	0.92	-0.05	-0.04	0.12
Hosp. based (%)	0.13	0.12	0.17	0.08	0.05	0.04	-0.12
Monthly patient volume							
Patients (#)	69.80	67.77	78.48	83.02	10.48*	8.43**	11.38*
In-center HD (#)	62.83	60.96	70.83	73.61	9.67	8.55**	8.69
HHD (#)	0.96	0.84	1.47	1.59	0.65*	-0.10	0.68
PD (#)	6.18	6.14	6.38	8.08	0.20	0.01	2.09***
Capacity and monthly congestion							
Stations (#)	17.29	17.13	17.96	21.15	0.80	-0.05	4.57*
Stats/pats (#)	0.77	0.76	0.81	0.43	0.05	0.10	-0.49*
Nurses/pats (#)	0.16	0.14	0.23	0.13	0.09	0.02	-0.14
PCTs/pats (#)	0.13	0.12	0.16	0.12	0.03	-0.05	-0.05
Diets/pats (#)	0.03	0.02	0.03	0.02	0.01	-0.00	-0.02*
Miles to nearest center							
To co-owned	12.76	12.65	13.28	13.92	0.68	2.10	-1.96
To competing	8.29	8.00	9.57	12.98	1.60	1.29	1.87
Monthly reported costs ($K) (2011-2016)							
Total	225	219	252	254	34	45***	21
Capital	37	36	42	41	6	6**	3
Staff	70	67	79	76	12	16**	3
Supply	24	23	28	30	5*	5**	4
Admin	55	54	59	62	6	10**	7
Other	40	39	45	45	6	9***	4
Fixed	92	90	101	103	11	16**	9
Average	3.4	3.4	3.4	3.3	0.0	-0.3***	-0.0
Sample composition							
Centers (#)	8,336	6,802	1,535	331	8,336	1,543	1,535
Center-months (#M)	0.91	0.74	0.17	0.04	0.91	0.25	0.17

Tab. 4. *Centers' characteristics (2004-2016).* This table reports descriptive statistics about dialysis centers. The sample consists of (center, month)-level observations. In columns (5)-(7), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are computed using state-level cluster-robust standard errors. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 10. Source: author's analysis of the USRDS Database and HCRIS data.

	Means				Regression-adjusted mean differences		
		CON?			CON vs. no CON		WA/NC vs. other CON
	Overall	No	Yes	WA/NC	Statewide	At borders	Statewide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Capacity and resident patient population							
Has center (%)	0.55	0.53	0.65	0.77	0.11*	-0.07	0.17**
Centers (#)	2.10	2.09	2.15	1.94	-0.33***	-0.34*	-0.19
Stations (#)	35	34	37	39	-4.52**	-5.04**	3.97
Patients (#)	127	122	152	147	-	-	-
Facility ownership							
Chains (#)	0.67	0.66	0.69	0.78	-0.01	-0.10	0.13
Ind. centers (#)	0.69	0.66	0.84	0.57	0.03	-0.11	-0.32
Owners (#)	1.36	1.32	1.53	1.35	0.03	-0.21	-0.19
Sample composition							
County-months (#M)	0.49	0.40	0.09	0.02	0.49	0.10	0.09
Counties (#)	3,144	2,572	572	139	3,144	414	572

Tab. 5. *Counties' dialysis patient and center characteristics (2004-2016).* This table reports descriptive statistics about counties. The sample consists of (county, month)-level observations. In columns (5)-(7), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are computed using state-level cluster-robust standard errors. See the discussion near page 10. Source: author's analysis of the USRDS Database.

	Applications in counties without incumbents	Applications in counties with incumbents		
		All	Spinoffs	Totally new
	(1)	(2)	(3)	(4)
RD	0.552**	0.432**	-0.383*	0.886***
	(0.219)	(0.195)	(0.213)	(0.084)
Bandwidth-L	2.0	1.0	1.0	1.0
Bandwidth-R	4.5	1.0	1.0	1.0
N	618	3,510	3,510	3,510
McCrary test (t)	-0.41	-0.81	-0.81	-0.81
McCrary test (p)	0.68	0.42	0.42	0.42

Tab. 6. *Effect of NC dialysis CON program thresholds.* This table reports estimates of the discontinuous change in application-filing rates associated with crossing the NC deficit threshold in counties without incumbents (column (1)) or both the NC deficit and minimum utilization thresholds in counties with incumbents (columns (2)-(4)). The outcome is an indicator equal to 1 if an application was filed and 0 otherwise. In counties with incumbents, applications may propose to spinoff existing stations to new locations (column (3)) or open totally new centers (column (4)). Figures 2 and 3 summarize this analysis graphically. See the discussion near page 13. Source: author's analysis of the NC dialysis CON program SDRs and application data.

	Mi. to Chosen Center (1)	Mi. to Nearest Center (2)	1[HHD] (3)	1[PD] (4)	1[Home] (5)
1[Has Center]	-8.670***	-10.490***	-0.023**	-0.053	-0.076**
	(1.565)	(1.860)	(0.011)	(0.037)	(0.036)
	[5.538]	[5.640]	[2.147]	[1.461]	[2.099]
ZCTA & month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	USA
Baseline Y	25.755	18.244	0.015	0.162	0.176
Reduced form	-4.691***	-5.590***	-0.012**	-0.028	-0.041**
First stage	0.541***	0.533***	0.533***	0.533***	0.533***
F-statistic	95.317	87.538	87.538	87.538	87.538
VtF 95% CV	1.918	1.916	1.919	1.921	1.921
Clusters (#)	1,743	1,743	1,744	1,744	1,744
Observations (#)	65,847,118	67,383,305	67,385,106	67,385,106	67,385,106
Unique patient-months in:					
Event counties (#)	78,797	80,271	80,271	80,271	80,271
Comp. counties (#)	5,867,165	5,988,933	5,989,062	5,989,062	5,989,062

	Stats/Pats At Chosen Center (6)	Nurs./Pats At Chosen Center (7)	1[Hosp.] (8)	1[URR <65%] (9)	Expected Utility (MTEs) (10)
1[Has Center]	0.105***	0.038***	-0.019	-0.007	10.560***
	(0.020)	(0.007)	(0.013)	(0.024)	(0.853)
	[5.215]	[5.668]	[1.530]	[0.295]	[12.383]
ZCTA & month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	Reg.
Baseline Y	0.227	0.060	0.182	0.101	54.122
Reduced form	0.057***	0.019***	-0.010	-0.003	6.028***
First stage	0.541***	0.500***	0.526***	0.447***	0.571***
F-statistic	95.318	43.730	79.717	30.832	84.692
VtF 95% CV	1.926	1.893	1.915	1.849	1.910
Clusters (#)	1,744	1,420	1,743	1,510	444
Observations (#)	65,849,227	33,349,389	54,686,612	34,143,752	8,453,167
Unique patient-months in:					
Event counties (#)	78,797	31,496	66,131	36,536	78,797
Comp. counties (#)	5,867,331	2,874,368	4,849,749	2,883,666	1,276,451

Tab. 7. *Marginal centers' effects on patient access, health, and welfare.* This table reports results from the IV-DID analysis. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. Comparison groups are nationwide or regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussions near pages 17 and 20. Source: author's analysis of the USRDS Database.

	Expected Utility (MTEs) (1)	Reported Fixed Costs (3)
1[Has Center]	358.680***	43568.129***
	(56.696)	(3820.682)
	[6.326]	[11.403]
County and month FE	Y	Y
Comparison group	Reg.	Reg.
Baseline Y	974.398	0.000
Reduced form	131.679***	15,994.833***
First stage	0.367***	0.367***
F-statistic	24.121	24.121
VtF 95% CV	2.152	2.330
Clusters (#)	449	449
Observations (#)	729,876	729,876
Unique county-months in:		
Event counties (#)	3,744	3,744
Comp. counties (#)	87,166	87,166

Tab. 8. *Marginal centers' effects on countywide patient welfare and fixed costs.* This table reports results from the IV-DID analysis. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Comparison groups are regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussions near pages 20 and 21. Source: author's analysis of the USRDS Database and HCRIS data.

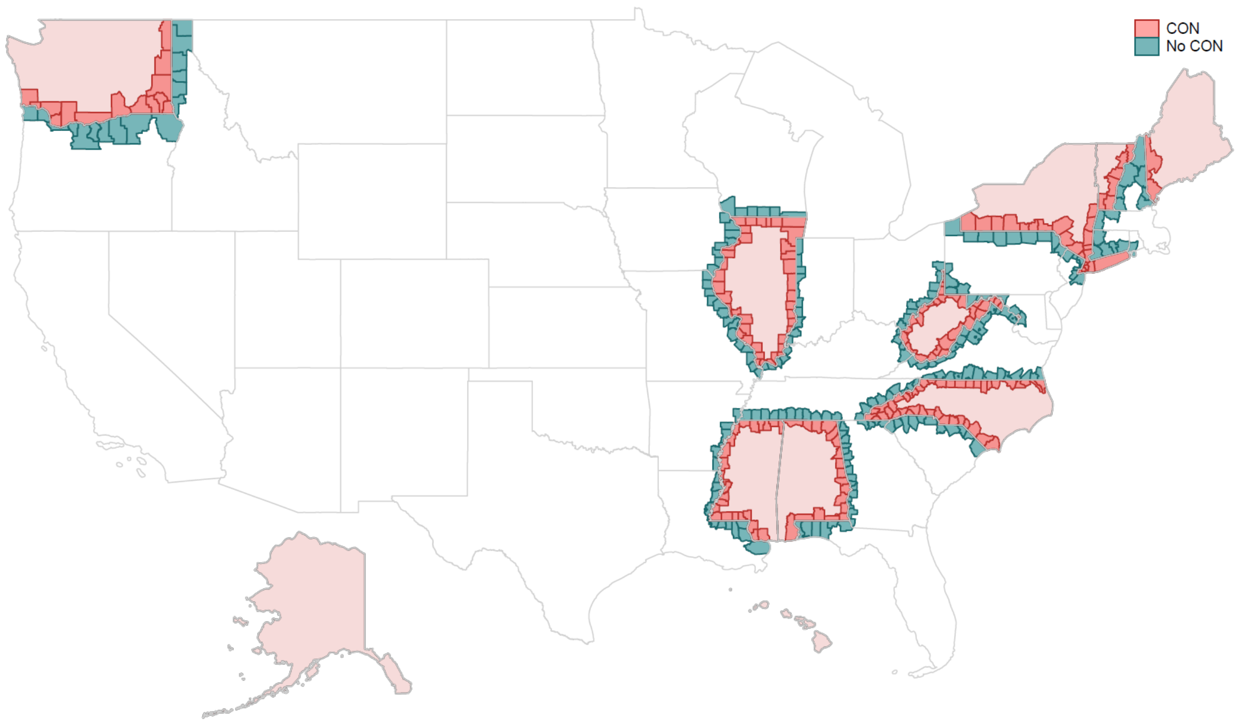
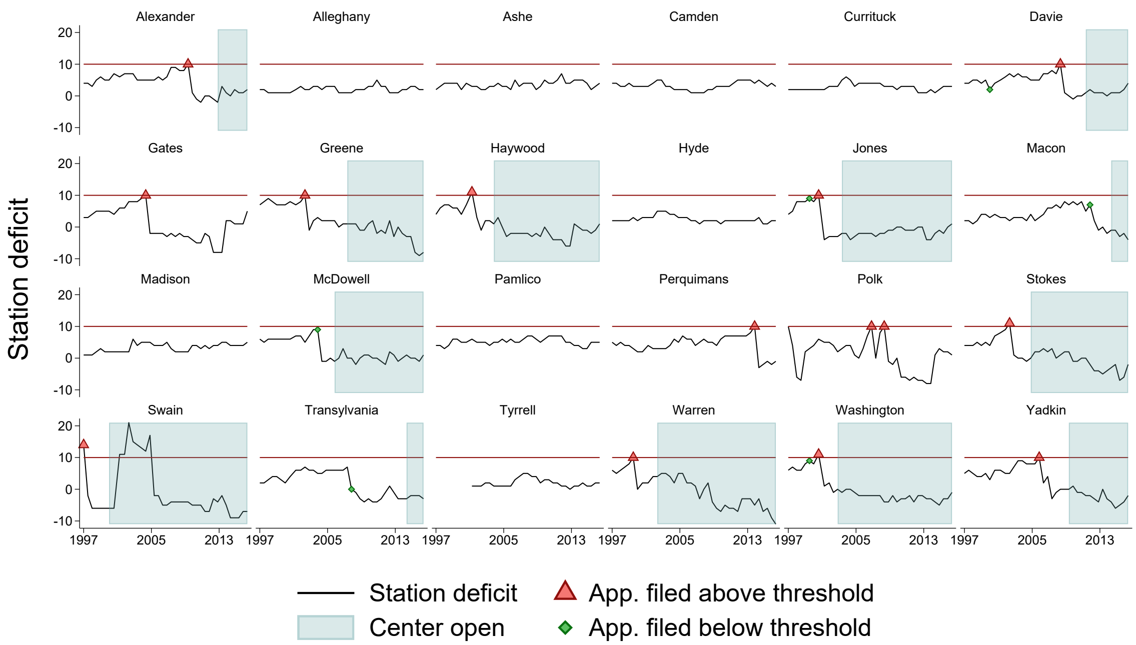
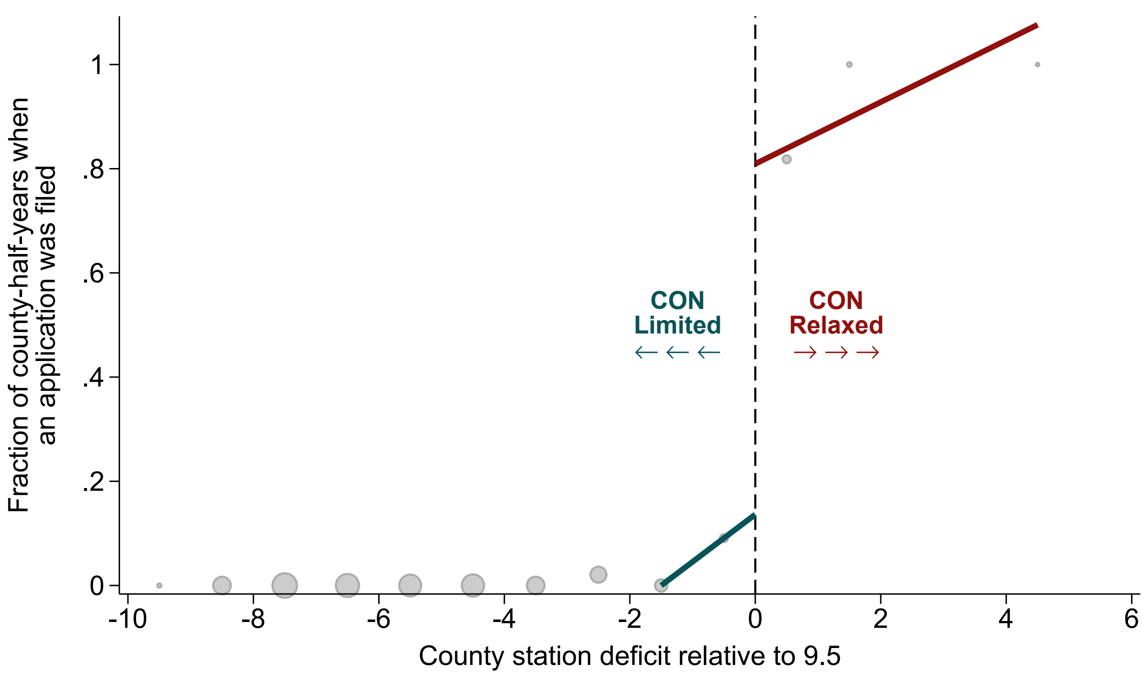


Fig. 1. *Cross-sectional variation in dialysis CON indicator (2004-2016).* This map identifies the states with and without dialysis CON programs and the counties on their borders. See the discussion near page 9. Source: AHPA surveys in 2004, 2005, 2010, 2012, and 2016.



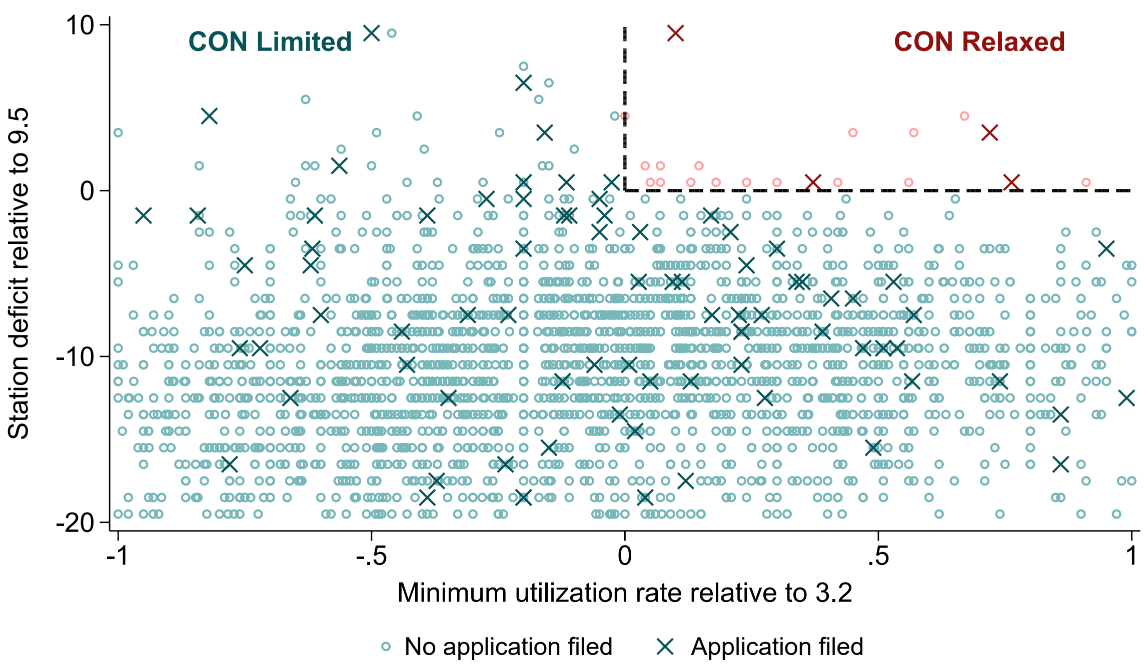
(a) Station deficit time series



(b) Application-filing regression discontinuity

Fig. 2. *Effect of NC dialysis CON program in counties without incumbents (1997-2019).* This figure plots application and need determination data from the NC dialysis CON program. Panel (a) identifies the 24 NC counties without incumbents in 1997. It shows that applications to open new centers are consistently filed after these counties cross the NC deficit threshold. Panel (b) plots the results of the corresponding RD analysis. See the discussion near page 13. Source: author's analysis of the NC dialysis CON program's application data and dialysis reports.

(a) Applications to enter with all new stations



(b) Applications to enter with existing stations

Fig. 3. *Effect of NC dialysis CON program in counties with incumbents (1997-2019).* This figure plots application and need determination data from the NC dialysis CON program. Panel (a) identifies applications to open new centers and panel (b) identifies applications to open centers with existing stations. They suggest that the NC deficit and minimum utilization thresholds were binding on potential entrants but not incumbents. See the discussion near page 13. Source: author's analysis of the NC dialysis CON program's application data and dialysis reports.

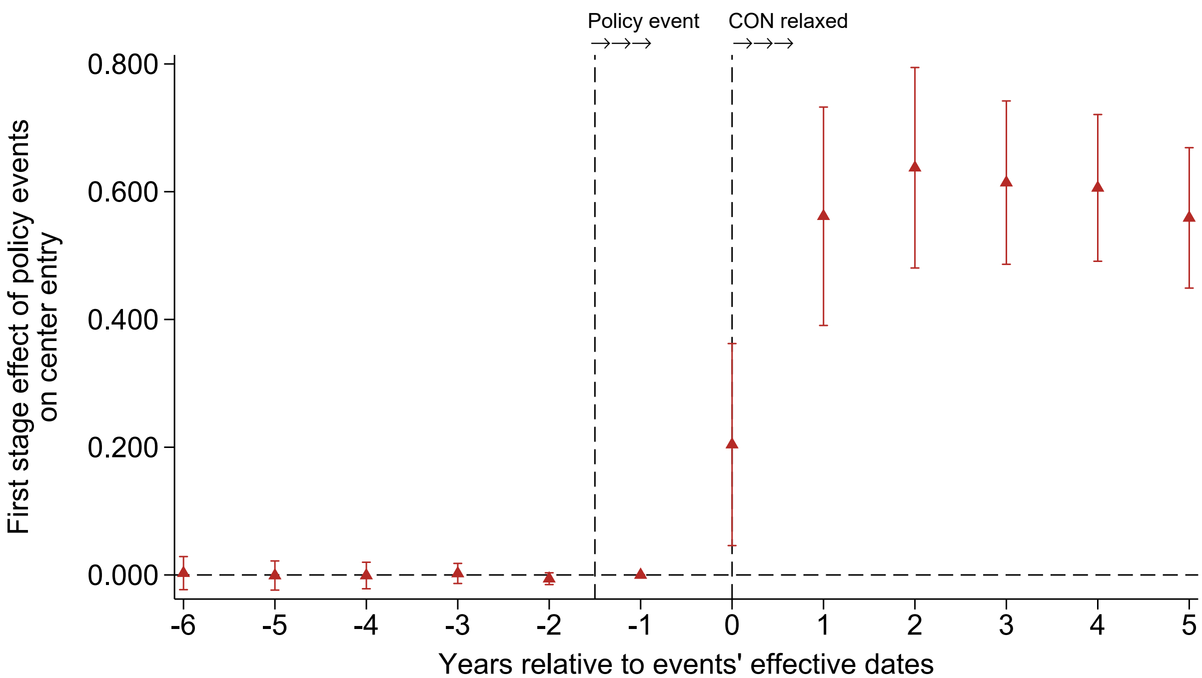
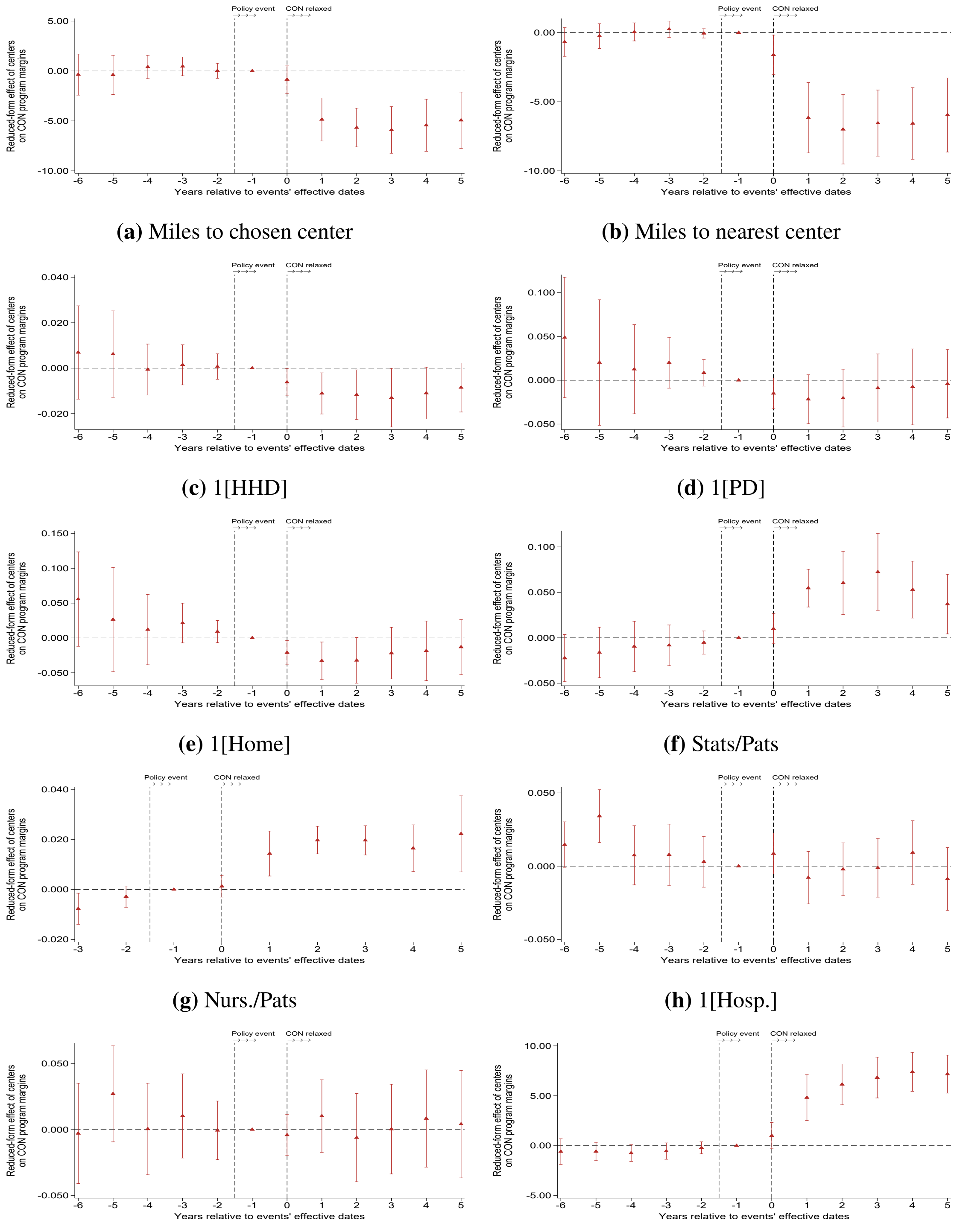


Fig. 4. *First stage effect of WA and NC dialysis CON events on entry.* This figure plots results from the IV-DID analysis. The outcome is an indicator equal to 1 if a patient has a center in their county and 0 otherwise. The bars are 95% confidence intervals computed using county-level cluster-robust standard errors. The dashed lines mark the events' actual and effective dates in relative time. Since the events could not cause centers to open instantaneously, I assume that their effective dates are 18 months later. The model includes patient characteristics (age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year). The comparison group is nationwide counties without centers on the events' effective dates. See the discussion near page 17. Source: author's analysis of the USRDS Database.



(a) Miles to chosen center **(b)** Miles to nearest center

(c) 1[HHD] **(d)** 1[PD]

(e) 1[Home] **(f)** Stats/Pats

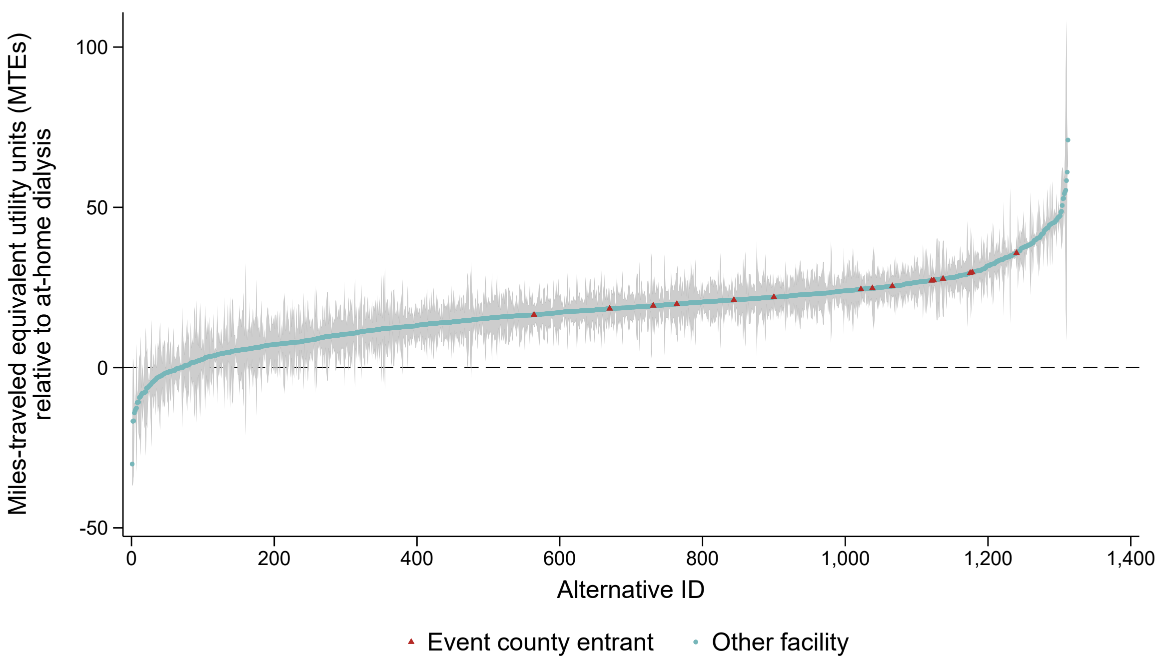
(g) Nurs./Pats **(h)** 1[Hosp.]

(i) 1[URR<65%] **(j)** Exp. Util. (MTEs)

Fig. 5. *Reduced-form effect of WA and NC dialysis CON events on patient access, health, and welfare*. This figure plots results from the IV-DID analysis. The bars are 95% confidence intervals computed with county-level cluster-robust standard errors. The dashed lines mark the events' actual and effective dates in relative time. Since the events could not cause centers to open instantaneously, I assume that their effective dates are 18 months later. Panel (g) uses a shorter window because staffing data are not available before 2004. See table 7 and the discussion near page 17. Source: author's analysis of the USRDS Database.

	(1)
TrDist	-0.109***
	(0.002)
1[Stay]	5.875***
	(0.036)
Cases (#)	1,368,224
Alts. (#)	1,312
Observations (#)	27,881,747
Clusters (#)	447
Alts. per case:	
Avg. (#)	20
Min. (#)	2
Max. (#)	93

(a) Travel and switching cost estimates



(b) Distribution of alternative-specific fixed effect estimates

Fig. 6. *Estimates of treatment choice model.* Panel (a) reports estimates of γ and λ in equation (5). County-level cluster-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel (b) plots the distribution of alternative-specific fixed effects scaled by $-\hat{\gamma}$. Shaded areas are 95% confidence intervals. See the discussion near page 20. Source: author's analysis of the USRDS database.

ONLINE APPENDIX

Summary of sections in the online appendix

- Appendix A describes how I constructed key variables.
- Appendix B reports additional descriptive statistics.
- Appendix C describes details about the 2007 WA policy change and NC threshold-crossings.
- Appendix D describes how IV-DID identifies CATE-ES in this context.
- Appendix E reports IV-DID estimates for additional outcomes
- Appendix F describes the results of the sensitivity analyses.

A Key Variables

As described in section 3, this study is based primarily on data from the U.S Renal Data System 2018 Database (USRDS Database) (USRDS 2018). The USRDS Database contains a number of standard analysis files (SAFs) produced by the USRDS using data from the Centers for Medicare and Medicaid Services (CMS), including Medicare claims, the chronic renal disease medical evidence reports, death notification reports, and dialysis center surveys. It also contains institutional Medicare claims data (USRDS IMCD). See USRDS (2018) for more information about the USRDS Database. Other vintages of the USRDS Database have been used in several studies, including Eliason et al. (2022) and Eliason et al. (2020). I also rely on data from the NC dialysis CON program, CMS's Healthcare Cost Report Information System (HCRIS), and several ancillary sources, including the National Bureau of Economic Research (NBER)'s ZCTA distances database, the NBER and Centers for Medicare and Medicaid Services (CMS)'s diagnosis-related group (DRG) to Major Diagnostic Category (MDC) crosswalks, the UDS Mapper ZIP-to-ZCTA crosswalk, and the U.S. Census Bureau's ZCTA-to-county relationship file.

In this section, I describe how I used these data to generate this study's key variables.

A.1 Patients' dialysis centers and modalities

The USRDS Database's RXHist SAF contains spell-level data, where each observation contains a patient ID, center ID, modality, start date, and end date. Each spell within a patient-center pair is mutually exclusive. I used these data to construct a (patient, month, center)-level dataset containing for each patient-month an observation for every center where they had a dialysis spell.

Each patient-month-center observation is associated with a treatment modality. I coarsened the modality indicator into 7 groups: (1) any dialysis, (2) in-center hemodialysis (HD), (3) continuous ambulatory peritoneal dialysis (CAPD), (4) continuous cycling peritoneal dialysis (CCPD), (5) any peritoneal dialysis (PD), (6) home hemodialysis (HHD), and (7) any home dialysis (PD or HHD).

In (patient, month)-level data, I assign each patient-month to that center with the earliest spell start date. (Patients are often associated with multiple centers in a given month when they switch centers during that month.) I allow each patient-month to be associated with multiple modalities when applicable.

A.2 Patients' payers

The USRDS Database's Payer SAF contains spell-level data, where each observation contains a patient ID, payer category, start date, and end date. Each patient's spells are mutually exclusive. I used these data to construct a (patient, month)-level dataset indicating each patient's payer category in that month and whether they were dual-eligible. When a patient had more than one payer in a given month, I assigned their payer in that month to be whichever had the earliest start date.

The payer categories are (1) HMO, (2) Medicare primary (parts A and B), (3) Medicare primary (other), (4) Medicare secondary with employer-sponsored group health plan (EGHP), (5) Medicare secondary with no EGHP, and (6) 90-day waiting period. (The waiting period refers to the 3 month delay between the onset of ESRD and Medicare coverage.) I defined a patient-month to have had FFS Medicare as a primary payer if it is associated with Medicare primary (parts A and B).

A.3 Patients' residences

The USRDS Database's Residence SAF contains spell-level data, where each observation contains a patient ID, ZIP code, county FIPS code, state FIPS code, start date, and end date. Each patient's spells are mutually exclusive. I used these data to construct a (patient, month)-level dataset indicating each patient's residence in that month. The start date of each patient's first observed spell is always missing. I treat it as beginning at the start of the sample period. Likewise, the end date of each patient's last observed spell is always missing. I treat it as ending at the end of the sample period. When a patient had more than one residence in a given month, I assigned their residence in that month to be whichever had the earliest start date.

A.4 ZCTA-to-county crosswalk

The U.S. Census Bureau's 2010 ZCTA-to-county relationship file contains (ZCTA, county)-level data, where each observation contains the number of residents shared between the ZCTA and the county. I used these data to create a ZCTA-level crosswalk between ZCTAs and counties by linking each ZCTA to the county where the largest share of its population resided.

A.5 ZIP-to-ZCTA crosswalk

The UDS Mapper is an online data clearinghouse affiliated with the U.S. Department of Health & Human Services' Health Resources & Services' Administration. It publishes a ZIP-to-ZCTA crosswalk linking ZIP codes to ZCTAs. I downloaded the crosswalk in June 2020. It contained data for years 2010-2019. I used the 2010 subsample for years prior to 2010.

A.6 Dialysis centers' characteristics

The USRDS Database's Facility SAF contains (center, year)-level data, where each observation contains a variety of business records, including the center's ZIP code, state FIPS code, certification date, number of stations, staffing, for-profit indicator, chain affiliation (if any), and a hospital-based indicator in that year. I combined these data with the RXHist SAF to construct a (center, month)-level dataset with an observation for each center-month in the RXHist SAF.

First, since the Facility SAF identifies each center-year's ZIP code but not its county, I used the ZIP-to-ZCTA crosswalk and the ZCTA-to-county crosswalk to link each center-year with a county. Second, when a center-year in the Facility SAF has a missing chain affiliation, I assume that it is an independent (non-chain) center.

Third, the Facility SAF contains staffing data beginning in 2004, including the number of full-time and part-time registered nurses (RNs), licensed practical nurses (LPNs), advanced practice nurses (APNs), patient care technicians (PCTs), social workers, and dieticians. Within each job category, I computed the total number of staff as the sum of the number of full-time staff plus 0.5 times the number of part-time staff. I also summed the number of RNs, LPNs, and APNs to compute the total number of nurses.

Fourth, when a variable has a missing value for a given center-year, I fill it in with non-missing values associated with that center in adjacent years. (E.g., if a center is observed to have had 10 stations in 2010 and missing stations in 2009, I assume that it also had 10 stations in 2009.) I leave staffing variables as missing prior to 2004.

Fifth, I used the RXHist SAF to compute the number of patients treated at each center-month. I combined this measure with the stations and staffing data derived from the Facility SAF to compute each center-month's stations-per-patient and staff-per-patient.

Finally, I used the RXHist SAF to determine each center's opening date. In particular, I treat each center's opening date as the earlier of (1) their earliest observed certification date in the Facility SAF and (2) their earliest observed treatment date in the RXHist SAF. For each (center, month), I compute the center's age in that month relative to this opening date.

A.7 Dialysis centers' reported costs

The HCRIS data contains (center, fiscal year)-level data, where each observation contains dialysis centers' reported costs in one of several cost categories in a given fiscal year. I define a dialysis center's reported fixed cost as the sum of the costs reported in lines 1-4, 6, and 11 of Form CMS-265-11 Worksheet A. These lines encompass:

1. Line 1: Capital related costs - buildings and fixtures
2. Line 2: Capital related costs - movable equipment
3. Line 3: Operation & maintenance of plant

4. Line 4: Housekeeping

5. Line 6: Machine capital-related or rental & maintenance

6. Line 11: administrative & general

I evenly distribute their reported fixed costs across each day in their fiscal year and then aggregate them up to the (center, month)-level.

A.8 Travel distances

The NBER ZCTA distances database contains (ZCTA1, ZCTA2)-level data, where each observation contains the distance between the ZCTAs' centroids. Only ZCTA pairs that are within 100 miles of each other are included. I used this database to measure distances between dialysis centers' locations, and between dialysis centers' locations and patients' residences. In both cases, I used the UDS Mapper's ZIP-to-ZCTA crosswalk to determine the centers' and patients' ZCTAs. If a ZCTA pair is not observed in the ZCTA distances database but each ZCTA in the pair is observed in the database, then I set the travel distance for that pair to be 100 miles. Otherwise, I treat the distance as missing.

A.9 Claims-based measures

The IMCD contains Medicare claim-level data, where each observation contains a patient ID, provider ID, Health Care Finance Administration (HCFA) source of the bill, type of bill, claim start date, claim end date, diagnosis related group (DRG), and total Medicare paid amount. The data include Medicare claims from 1977-2016, but some data are missing prior to 1989.

I used these data to construct several claims-based measures. Throughout, I define claims-based measures for only those patient-months associated with FFS Medicare as the primary payer. I treat them as missing otherwise because they may have been covered by another payer. (For instance, a patient-month associated with HMO coverage may not have an observed hospital stay either because no hospital stay occurred or because it was paid for by a non-Medicare plan.)

A.9.1 Hospitalizations

I defined a claim to be a hospital claim if its HCFA source is an inpatient hospital stay or if its HCFA source is an outpatient stay but its type of bill indicates that it was an inpatient hospital stay. I defined a patient-month to have a hospitalization if I observed a hospital claim associated with that patient in that month. Since 1989, each claim in the IMCD is associated with a diagnosis-related group (DRG). I categorized hospital stays using the DRG to Major Diagnostic Category (MDC) crosswalk published by the NBER (1984-2013) and CMS (2014-2019) to link each claim's DRG with an MDC. There are 25 MDCs, including "circulatory system" and "infectious and parasitic diseases and disorders."

A.9.2 Medicare spending

Since 1989, each claim in the IMCD is associated with a total Medicare paid amount. I distributed each claim's total Medicare paid amount across the months associated with that claim in proportion to the number of that claim's days spent in that month. For instance, for a claim spanning March 28 through April 8, inclusive, I assigned one-third of the claim's paid amount to March and two-thirds to April. For each patient-month, I computed the total paid amount associated with that patient-month across all of their claims.

A.9.3 Dialysis sessions

Since 1989, some claims in the IMCD are associated with a number of dialysis sessions and indicators of treatment modality. I distributed each claim's sessions across the months associated with that claim in proportion to the number of that claim's days spent in that month. For instance, for a claim spanning March 28 through April 8, inclusive, I assigned one-third of the claim's sessions to March and two-thirds to April. For each patient-month, I computed the total number of sessions per modality associated with that patient-month across all of their claims. This process resulted in an improbable number of sessions for some patient-months (e.g., hundreds or thousands of sessions). When a patient-month is associated with more than 40 in-center HD or HHD sessions or more than 60 PD sessions, I treat these values as missing.

A.9.4 Urea reduction ratios

From 1998-2011, some claims in the IMCD are associated with a measure of their patients' urea reduction ratio (URR). The measure indicates whether the URR was <60%, 60-65%, 65-70%, 70-75%, or >75%. From 2012-2016, these indicators are in the USRDS Claims Clinical SAF. I append the data from these sources together to generate (patient, month)-level data spanning 1998-2016 and indicating whether each patient had a URR within any of the given ranges in that month.

A.10 Patients' demographics and other characteristics

The USRDS Database's Patient SAF contains records of each patient's sex, race, ethnicity, primary cause of ESRD, and date of birth. I generate an indicator for each sex, race, ethnicity, and primary cause of ESRD category. I also measure each patient's age in each month using their date of birth. I set age to missing for any patients ever associated with an age below 0 or greater than 105.

The USRDS Database's Death SAF contains records of each patient's date of death, if any. I define a patient to have died in a given month if their date of death falls in that month.

The USRDS Database's Medical Evidence SAF contains records of each patient's employment status, height, weight, and BMI at ESRD onset. I generate patient-level indicators for any employment (full-time or part-time), no employment (unemployed, homemaker, retired, medical leave-of-absence, and student), and other. I also generate patient-level measures of each patient's height, weight, and BMI. Some heights and weights are implausible for some patients (e.g., 0 kilograms or more than 1,000 kilograms). I set these to missing.

Finally, the USRDS Database's Transplant SAF contains records of each patient that ever received a kidney transplant.

A.11 North Carolina station deficits, minimum utilization rates, and application data

The NC dialysis CON program publishes facility-level and county-level data in semiannual dialysis reports (SDRs). The facility-level data include each center's patient volume, number of dialysis stations, and utilization rate. The county-level data include each county's current, lagged, and forecasted resident in-center dialysis patient population, number of dialysis stations, and station deficit. I collected SDRs spanning 1997-2019 and manually entered their facility-level and county-level data to produce a (county, half-year)-level dataset containing each county's station deficit and minimum utilization rate.

I also rely on contemporaneous records of applications for certificates-of-need filed with the NC dialysis CON program by existing centers and potential entrants. The data include the date that each application was filed, the applicant's name, the result of the review process (e.g., if the certificate-of-need was granted or denied), the project's location (usually this is the name of a dialysis center and a county), the project's projected cost, and the purpose of the project (e.g., to open a new center or add stations to an existing center). I manually reviewed all of the project descriptions and identified applications to open a center using all-new stations or using stations that had previously been approved at another location. Since applications may be filed in semiannual application cycles that begin after the publication of an SDR, I associate each application with the most recently published prior SDR.

B Additional descriptive statistics

In section 3, I reported descriptive statistics for the sample of county-months, patient-months, and center-months that I constructed from the USRDS Database and ancillary data sources. I reported the descriptive statistics for years 2004-2016 to align them with the cross-sectional analysis in section 4. In this section, I report descriptive statistics for the entire 1980-2016 sample period. The results are in tables A3-A7.

C Additional details about the 2007 WA reform and NC threshold-crossings

The NC dialysis CON program permits entry in counties without incumbents when their station deficits exceed 9.5. I obtained SDRs between 1997 and 2019. According to these records, 24 counties did not have an operating or previously-approved center in March 1997. Of these counties, Alexander, Davie, Gates, Greene, Haywood, Jones, Perquimans, Polk, Stokes, Swain, Warren, Washington, and Yadkin counties experienced a threshold-crossing between 1997 and 2019. I exclude Perquimans County from the IV-DID analysis because it crossed the station deficit threshold in January 2014 and the sample period ends shortly thereafter.

In Washington, a 2007 reform relaxed the WA dialysis CON program's entry limits in counties without incumbents in 2006. The target WA counties were Adams, Columbia, Douglas, Ferry, Garfield, Jefferson, Kittitas, Klickitat, Lincoln, Okanogan, Pacific, Pend Oreille, San Juan, Skamania, Stevens, and Wahakium counties (WA State Register 2006). However, according to the USRDS Database, Okanogan County had a center in 2006. Furthermore, according to records from the WA dialysis CON program, someone filed an application to open a new center in Kittitas County shortly before 2007. Although the application was reviewed after 2007, it was reviewed using pre-2007 rules. Therefore, I exclude Okanogan and Kittitas counties from the IV-DID analysis.

D Instrumental variables difference-in-differences

I leverage variation generated by the 2007 WA policy change and the NC threshold-crossings using instrumental variables difference-in-differences (IV-DID). This approach identifies the complier average treatment effect at the event site (CATE-ES) under the following assumptions.

Consider a setting with two periods $t \in \{1, 2\}$ and a mass of units (e.g., counties). Let there be some event (i.e., the 2007 WA policy change or a NC threshold-crossing) that is related to some treatment (i.e., having a dialysis center) and some outcome (e.g., health status). Let $Z_i \in \{0, 1\}$ indicate whether some unit i is exposed to the event. Let $D_i(Z) \in \{0, 1\}$ indicate unit i's potential treatment status in period 2. Since the event counties and comparison counties did not have dialysis centers prior to the events, we may assume that no units are exposed to the treatment in period 1 for simplicity. Finally, let $Y_{it}(D, Z)$ measure unit i's potential outcome in period t. Assume that $Y_{it}(D, Z) = Y_{it}(D)$ for all (D, Z) ("exclusion restriction").

Let $\mathcal{C} := \{i : D_i(1) - D_i(0) = 1\}$ be the set of compliers. These units would only experience the treatment if they experience the event. Let $\mathcal{D} := \{i : D_i(1) - D_i(0) = -1\}$ be the set of defiers. These units would only experience the treatment if they do not experience the event. Assume that $\mathcal{D} = \emptyset$ ("monotonicity"). Assume that $\mathcal{C} \neq \emptyset$ ("relevance").

Let $(Z_i, D_i, Y_{i1}, Y_{i2})$ be unit i's realized exposure to the event, treatment status, and outcomes. Assume that $\mathbb{E}[D_i(0)|Z_i = 1] = \mathbb{E}[D_i(0)|Z_i = 0]$ ("first stage mean independence"). This states that the average counterfactual treatment status in the event counties is equal to the average realized treatment status in the comparison counties. Assume that $\mathbb{E}[Y_{i1}(D_i(1))|Z_i = 1] = \mathbb{E}[Y_{i1}(D_i(0))|Z_i = 1]$ ("reduced form no anticipation"). This states that the average realized period 1 outcome in the event counties is equal to the average counterfactual period 1 outcome in the event counties. Finally, assume that $\mathbb{E}[Y_{i2}(D_i(0)) - Y_{i1}(D_i(0))|Z_i = 1] = \mathbb{E}[Y_{i2}(D_i(0)) - Y_{i1}(D_i(0))|Z_i = 0]$ ("reduced form parallel trends"). This states that the average counterfactual outcome trend in the event counties is equal to the average realized outcome trend in the comparison counties.

The reduced form effect is $\mathbb{E}[Y_{i2}(D_i(1)) - Y_{i2}(D_i(0))|Z_i = 1]$. It is identified by:

$$
\begin{aligned}
&\mathbb{E}[Y_{i2} - Y_{i1}|Z_i = 1] - \mathbb{E}[Y_{i2} - Y_{i1}|Z_i = 0] \qquad \text{(D.1)}\\
&\quad = \mathbb{E}[Y_{i2}(D_i(1))|Z_i = 1] - \mathbb{E}[Y_{i1}(D_i(1))|Z_i = 1] - \mathbb{E}[Y_{i2}(D_i(0)) - Y_{i1}(D_i(0))|Z_i = 0]\\
&\quad = \mathbb{E}[Y_{i2}(D_i(1))|Z_i = 1] - \mathbb{E}[Y_{i1}(D_i(0))|Z_i = 1] - \mathbb{E}[Y_{i2}(D_i(0)) - Y_{i1}(D_i(0))|Z_i = 1]\\
&\qquad\quad \text{by reduced form no anticipation and parallel trends}\\
&\quad = \mathbb{E}[Y_{i2}(D_i(1)) - Y_{i2}(D_i(0))|Z_i = 1]
\end{aligned}
$$

Likewise, the first stage effect is $\mathbb{E}\left[D_i(1) - D_i(0)|Z_i = 1\right]$. It is identified by:

$$\begin{aligned}
&\mathbb{E}\left[D_i|Z_i = 1\right] - \mathbb{E}\left[D_i|Z_i = 0\right] \\
&\quad = \mathbb{E}\left[D_i(1)|Z_i = 1\right] - \mathbb{E}\left[D_i(0)|Z_i = 0\right] \\
&\quad = \mathbb{E}\left[D_i(1)|Z_i = 1\right] - \mathbb{E}\left[D_i(0)|Z_i = 1\right] \\
&\qquad \text{by first stage mean independence} \\
&\quad = \mathbb{E}\left[D_i(1) - D_i(0)|Z_i = 1\right]
\end{aligned} \tag{D.2}$$

Finally, the parameter of interest is CATE-ES $:= \mathbb{E}\left[Y_{i2}(1) - Y_{i2}(0)|i \in C, Z_i = 1\right]$. It is identified under the foregoing assumption by the ratio of the reduced form effect (D.1) and the first stage effect (D.2), as follows:

$$\begin{aligned}
&\frac{\mathbb{E}\left[Y_{i2} - Y_{i1}|Z_i = 1\right] - \mathbb{E}\left[Y_{i2} - Y_{i1}|Z_i = 0\right]}{\mathbb{E}\left[D_i|Z_i = 1\right] - \mathbb{E}\left[D_i|Z_i = 0\right]} \\
&\quad = \frac{\mathbb{E}\left[Y_{i2}(D_i(1)) - Y_{i2}(D_i(0))|Z_i = 1\right]}{\mathbb{E}\left[D_i(1) - D_i(0)|Z_i = 1\right]} \\
&\quad = \frac{\mathbb{E}\left[Y_{i2}(1) - Y_{i2}(0)|i \in C, Z_i = 1\right]\mathbb{P}(i \in C|Z_i = 1)}{\mathbb{P}(i \in C|Z_i = 1)} \\
&\qquad \text{by monotonicity and relevance} \\
&\quad = \mathbb{E}\left[Y_{i2}(1) - Y_{i2}(0)|i \in C, Z_i = 1\right]
\end{aligned} \tag{D.3}$$

Figure A4 illustrates this identification strategy with a stylized example. Panel (a) plots the first-stage event study. It shows that under the first stage mean independence and relevance assumptions, the first-stage DID identifies $\mathbb{E}\left[D_i(1) - D_i(0)|Z_i = 1\right]$. In the illustration, this is denoted by γ and is equal to 0.3. Panel (b) plots the reduced-form event study. It shows that under the reduced form no anticipation and parallel trends assumptions, the reduced-form DID identifies $\mathbb{E}\left[Y_{i2}(D_i(1)) - Y_{i2}(D_i(0))|Z_i = 1\right]$. In the illustration, this is denoted by δ and is equal to 3. Under the monotonicity and exclusion restriction assumptions, the ATT of Z on Y (δ) is entirely attributable to the effect of Z on X (γ). Therefore, the ratio $\delta/\gamma = 3/0.3 = 9$ is the CATE-ES.

E Additional IV-DID outcomes

In section 6.4, I reported IV-DID results for several access, treatment choice, and health outcomes. Table A8 and figure A2 report results for several additional outcomes.

F Sensitivity analysis

In section 6.5 and 6.6, I described the results of several sensitivity analyses. In this section, I report the results of the sensitivity analyses in full.

F.1 IV-DID sensitivity to control variables

Table A9 reproduces the IV-DID analysis, excluding patient-level control variables.

F.2 IV-DID sensitivity to comparison counties

Table A10 reproduces the IV-DID analysis, replacing the national comparison counties with regional comparison counties.

F.3 IV-DID sensitivity to pooling WA and NC

Table A11 reproduces the IV-DID analysis for the 2007 WA reform only. Table A12 reproduces the IV-DID analysis for the NC threshold-crossings only.

F.4 Choice model sensitivity to linear travel cost

Figure A3 reproduces the choice model estimates using a quadratic measure of patients' distances to their alternatives. That is, I estimate

$$u_{ijt} = \gamma_1 \mathrm{TrDist}_{ijt} + \gamma_2 \mathrm{TrDist}^2_{ijt} + \lambda_j \mathrm{Stay}_{ijt} + \delta_{jt} + \varepsilon_{ijt} \tag{F.4}$$

As in section 6.6, I assume that $\lambda_j = \lambda$ and $\delta_{jt} = \delta_j$ for all j, t in order to reduce the computational cost.

County	Stations	Policy Regime	Projected Patients Needed For Given Num. of Stations	Resident Patient Populations from the Target WA Counties (pre) and the Neighboring Target WA Counties (post) 2007	2008	2009	2010	2012	2015
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)	(8)	(9)
1. Stevens	10	Pre	48	12	15	20	25	29	38
		Post	32	31	36	44	41	51	70
2. Adams	5	Pre	24	15	17	15	17	17	19
		Post	16	20	22	21	22	20	28
3. Pacific	10	Pre	48	22	23	24	24	17	24
		Post	32	28	26	28	28	22	28
4. Jefferson	6	Pre	29	13	<11	<11	11	16	18
		Post	19	14	<11	11	13	16	20
5. Douglas	8	Pre	38	34	35	31	30	33	31
		Post	26	34	35	31	30	33	31

Tab. A1. *Characteristics of entrants in the target WA counties.* This table presents characteristics of the centers that opened in the target WA counties after the 2007 reform and the counties' resident patient populations. Before the reform, station deficits were computed using each county's resident in-center dialysis patient population and an assumption that each station could serve 4.8 patients. After the reform, station deficits were computed using each county's resident in-center dialysis patient population, each neighboring target WA county's resident in-center dialysis patient population while the neighboring county does not have a center, and an assumption that each station could serve 3.2 patients. Squares indicate years when the new centers were operational. Statistics are omitted for cells that consist of fewer than 11 individuals. See the discussion near page 17. Source: author's analysis of the USRDS Database and the Medicare Dialysis Facility Compare files.

	Reported Fixed Costs
#[HD Patients]	0.011593***
	(0.000417)
#[HD Patients]^2	-0.000013***
	(0.000003)
#[Home Patients]	0.008636***
	(0.000321)
#[Home Patients]^2	-0.000011***
	(0.000002)
#[Stations]	0.026473***
	(0.001907)
#[Stations]×#[HD Patients]	-0.000123***
	(0.000024)
%[County rural pop.]	-0.001472***
	(0.000166)
Age FE	Y
Chain-by-trend FE	Y
State FE	Y
Observations	400,395
Clusters (#)	6,452
Baseline Y	91,624
R^2	0.757

Tab. A2. *Estimates of reported fixed cost prediction model.* This table presents estimates of a linear regression model relating log reported fixed costs to dialysis center characteristics. Baseline Y is the sample average value of the outcome. See the discussion near page 21. Source: author's analysis of the USRDS Database and HCRIS data.

	N (1)	Mean (2)	SD (3)	5%ile (4)	Median (5)	95%ile (6)
Age, race, ethnicity, and sex						
Age[1]	108,891,800	60.10	15.63	32.00	62.00	83.00
White (%)	2,852,343	0.66	0.47	0.00	1.00	1.00
Black (%)	2,852,343	0.29	0.45	0.00	0.00	1.00
AIAN (%)	2,852,343	0.01	0.10	0.00	0.00	0.00
Asian (%)	2,852,343	0.03	0.17	0.00	0.00	0.00
NHPI (%)	2,852,343	0.01	0.09	0.00	0.00	0.00
Hispanic (%)	2,852,343	0.11	0.31	0.00	0.00	1.00
Not hispanic (%)	2,852,343	0.75	0.43	0.00	1.00	1.00
Female (%)	2,852,343	0.45	0.50	0.00	0.00	1.00
Male (%)	2,852,343	0.55	0.50	0.00	1.00	1.00
Employment status at ESRD onset						
Some empl. (%)	2,852,343	0.08	0.27	0.00	0.00	1.00
No empl. (%)	2,852,343	0.67	0.47	0.00	1.00	1.00
Height and weight at ESRD onset						
Height (cm)	2,162,934	168.00	11.62	150.00	168.00	185.42
Weight (kg)	2,171,303	79.75	24.26	47.63	76.00	124.00
BMI	2,127,998	28.35	7.81	18.50	26.87	43.21
Primary cause of ESRD						
Diabetes (%)	2,852,343	0.42	0.49	0.00	0.00	1.00
Hypertension (%)	2,852,343	0.28	0.45	0.00	0.00	1.00
Glomer. (%)	2,852,343	0.11	0.31	0.00	0.00	1.00
Cyst. kidney (%)	2,852,343	0.02	0.15	0.00	0.00	0.00
Sample composition						
Patient-months (#)	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574
Patients (#)	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343

Tab. A3. *Patients' demographic and biographic characteristics (1980-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of patient-level observations. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 52. Source: author's analysis of the USRDS Database.
[1] Estimated from a (patient, month)-level sample.

	N (1)	Mean (2)	SD (3)	5%ile (4)	Median (5)	95%ile (6)
Miles to nearest alternatives						
Any alternative	107,808,188	4.55	7.82	0.00	1.96	18.94
With >med. stats/pats	107,808,188	9.15	13.50	0.00	4.36	33.97
Alternatives within 100 miles						
Centers (#)	107,786,177	135.78	116.74	14.00	100.00	409.00
Ind. centers (#)	107,786,177	53.97	59.96	4.00	31.00	208.00
Chains (#)	107,786,177	4.53	2.14	1.00	5.00	8.00
Owners (#)	107,786,177	58.50	61.03	6.00	35.00	216.00
Chosen center characteristics						
Distance (mi)	106,537,421	11.82	20.18	0.00	5.40	52.05
Stats/pats (#)	107,718,973	0.25	0.48	0.11	0.21	0.44
Nurses/pats (#)[1]	62,248,996	0.07	0.11	0.03	0.06	0.15
PCTs/pats (#)[1]	62,248,996	0.08	0.10	0.01	0.08	0.13
Diets/pats (#)[1]	62,248,996	0.01	0.01	0.00	0.01	0.02
Not switched (%)	106,185,352	0.98	0.15	1.00	1.00	1.00
Switched (%)	106,185,352	0.02	0.15	0.00	0.00	0.00
Treatment modalities						
In-center HD (%)	108,988,574	0.89	0.32	0.00	1.00	1.00
PD (%)	108,988,574	0.11	0.31	0.00	0.00	1.00
HHD (%)	108,988,574	0.01	0.12	0.00	0.00	0.00
Ever TX (%)[2]	2,852,343	0.14	0.34	0.00	0.00	1.00
Sample composition						
Patient-months (#)	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574
Patients (#)	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343

Tab. A4. *Patients' treatment choices (1980-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of (patient, month)-level observations. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 52. Source: author's analysis of the USRDS Database.

[1] Staffing data is only available in 2004-2016.

[2] Estimated from a patient-level sample.

	N	Mean	SD	5%ile	Median	95%ile
	(1)	(2)	(3)	(4)	(5)	(6)
Health insurance enrollment and spending						
MCare FFS Prim. (%)	108,988,574	0.73	0.44	0.00	1.00	1.00
HMO (%)	108,988,574	0.09	0.28	0.00	0.00	1.00
Any Medicare (%)	108,988,574	0.81	0.39	0.00	1.00	1.00
Dual eligible (%)	108,988,455	0.33	0.47	0.00	0.00	1.00
Medicare spending ($)[1,2]	73,238,152	4,590.17	6,981.34	69.00	2,471.00	16,737.09
Dialysis sessions						
In-center HD (#)[1,2]	73,201,631	10.46	4.90	0.00	13.00	14.00
HHD (#)[1,2]	73,229,958	0.15	1.62	0.00	0.00	0.00
PD (#)[1,2]	73,205,039	1.73	6.71	0.00	0.00	13.29
Urea reduction ratio (URR)						
URR <65% (%)[1,3]	50,141,537	0.09	0.29	0.00	0.00	1.00
URR 65-75% (%)[1,3]	50,141,537	0.46	0.50	0.00	0.00	1.00
URR >75% (%)[1,3]	50,141,537	0.44	0.50	0.00	0.00	1.00
Hospitalizations and mortality						
Any (%)[1]	73,238,152	0.17	0.38	0.00	0.00	1.00
Circulatory (%)[1,2]	73,238,152	0.07	0.25	0.00	0.00	1.00
Kidney and UT (%)[1,2]	73,238,152	0.02	0.15	0.00	0.00	0.00
Infections (%)[1,2]	73,238,152	0.01	0.12	0.00	0.00	0.00
Died (%)	108,988,574	0.02	0.13	0.00	0.00	0.00
Sample composition						
Patient-months (#)	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574	108,988,574
Patients (#)	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343	2,852,343

Tab. A5. *Patients' health outcomes and spending (1980-2016).* This table reports descriptive statistics about dialysis patients. The sample consists of (patient, month)-level observations. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 52. Source: author's analysis of the USRDS Database.

[1] Sub-sample associated with Medicare FFS as a primary payer.

[2] Claims-based measures available in 1989-2016.

[3] URR data available in 1998-2016.

	N	Mean	SD	5%ile	Median	95%ile
	(1)	(2)	(3)	(4)	(5)	(6)
Age and chain affiliation						
Age	1,841,559	14.38	10.96	0.92	11.92	36.25
Davita (%)	1,711,349	0.17	0.38	0.00	0.00	1.00
Fresenius (%)	1,711,349	0.22	0.41	0.00	0.00	1.00
Small chain (%)	1,711,349	0.15	0.35	0.00	0.00	1.00
Independent (%)	1,711,349	0.46	0.50	0.00	0.00	1.00
Profit status and hospital affiliation						
For-profit (%)	1,684,945	0.72	0.45	0.00	1.00	1.00
Not for-profit (%)	1,684,945	0.28	0.45	0.00	0.00	1.00
Freestanding (%)	1,691,304	0.78	0.41	0.00	1.00	1.00
Hosp. based (%)	1,691,304	0.22	0.41	0.00	0.00	1.00
Monthly patient volume						
Patients (#)	1,841,559	60.47	52.90	1.00	49.00	160.00
In-center HD (#)	1,841,559	53.55	46.31	1.00	45.00	140.00
HHD (#)	1,841,559	0.84	5.12	0.00	0.00	4.00
PD (#)	1,841,559	6.26	13.67	0.00	0.00	33.00
Capacity and monthly congestion						
Stations (#)	1,709,641	16.02	8.85	4.00	15.00	32.00
Stats/pats (#)	1,709,641	1.05	3.40	0.10	0.26	5.75
Nurses/pats (#)[1]	894,724	0.16	0.74	0.03	0.07	0.31
PCTs/pats (#)[1]	894,724	0.13	0.70	0.00	0.08	0.17
Diets/pats (#)[1]	894,724	0.03	0.09	0.00	0.01	0.06
Miles to nearest center						
To Co-owned[2]	922,646	14.65	18.97	0.00	7.80	50.24
To Competing	1,709,105	8.99	14.85	0.00	2.64	38.32
Monthly reported costs ($K)						
Total[3]	403,710	224,791.42	136,542.97	71,761.43	194,322.46	479,484.79
Capital[3]	403,710	36,959.64	20,505.16	10,862.15	33,797.77	72,003.74
Staff[3]	403,710	69,513.64	51,029.03	14,931.15	57,384.65	166,276.60
Supply[3]	403,710	23,927.80	21,268.38	4,867.47	17,766.48	64,340.49
Admin[3]	403,710	54,695.15	32,518.03	16,463.63	48,117.95	114,823.64
Other[3]	403,710	39,695.19	28,404.05	7,681.97	33,432.20	92,461.32
Fixed[3]	403,710	91,654.80	49,187.05	30,590.04	82,574.49	179,441.53
Average[3]	403,710	3,375.40	4,222.92	2,268.45	2,949.91	4,837.02
Sample composition						
Centers (#)	12,425	12,425	12,425	12,425	12,425	12,425
Center-months (#)	1,841,559	1,841,559	1,841,559	1,841,559	1,841,559	1,841,559

Tab. A6. *Centers' characteristics (1980-2016).* This table reports descriptive statistics about dialysis centers. The sample consists of (center, month)-level observations. The sum of shares may exceed 1 due to rounding. Shares of "other" and "unknown" categories are omitted. See the discussion near page 52. Source: author's analysis of the USRDS Database and HCRIS data.

[1] Staffing data only available in 2004-2016.

[2] Only defined for chain-owned centers.

[3] Only available during 2011-2016.

	N	Mean	SD	5%ile	Median	95%ile
	(1)	(2)	(3)	(4)	(5)	(6)
Capacity and resident patient population						
Has Center (%)	1,395,012	0.42	0.49	0.00	0.00	1.00
Centers (#)	1,395,012	1.40	4.98	0.00	0.00	6.00
Stations (#)	1,395,012	21.44	87.09	0.00	0.00	90.00
Patients (#)	1,395,012	76.82	346.07	0.00	15.00	286.00
Facility ownership						
Chains (#)	1,395,012	0.36	0.72	0.00	0.00	2.00
Ind. centers (#)	1,395,012	0.70	2.74	0.00	0.00	3.00
Owners (#)	1,395,012	1.06	3.06	0.00	0.00	4.00
Sample composition						
County-months (#)	1,395,012	1,395,012	1,395,012	1,395,012	1,395,012	1,395,012
Counties (#)	3,144	3,144	3,144	3,144	3,144	3,144

Tab. A7. *Counties' dialysis patient and center characteristics (1980-2016).* This table reports descriptive statistics about counties. The sample consists of (county, month)-level observations. See the discussion near page 52. Source: author's analysis of the USRDS Database.

	HD Sess. for HD Pats. (1)	Medicare spending (2)	1[Died] (3)
1[Has Center]	-0.176	-146.797	0.002
	(0.226)	(181.688)	(0.002)
	[0.778]	[0.808]	[1.164]
ZCTA and month FE	Y	Y	Y
Patient characteristics	Y	Y	Y
Comparison group	USA	USA	USA
Baseline Y	12.114	4,004.713	0.018
Reduced form	-0.092	-77.248	0.001
First stage	0.523***	0.526***	0.533***
F-statistic	72.164	79.717	87.538
VtF 95% CV	1.910	1.915	1.921
Clusters (#)	1,741	1,743	1,744
Observations (#)	46,671,276	54,686,612	67,385,106
Unique patient-months in:			
Event counties (#)	57,687	66,131	80,271
Comp. counties (#)	4,078,323	4,849,749	5,989,062

Tab. A8. *Marginal centers' effects on additional outcomes.* This table reports the additional results of the IV-DID analysis. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. Comparison groups are nationwide or regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussions near pages 17 and 20. Source: author's analysis of the USRDS Database and HCRIS data.

	Mi. to Chosen Center (1)	Mi. to Nearest Center (2)	1[HHD] (3)	1[PD] (4)	1[Home] (5)
1[Has Center]	-8.572***	-10.469***	-0.022**	-0.048	-0.071*
	(1.599)	(1.865)	(0.011)	(0.037)	(0.036)
	[5.363]	[5.612]	[2.030]	[1.313]	[1.939]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	N	N	N	N	N
Comparison group	USA	USA	USA	USA	USA
Baseline *Y*	25.755	18.244	0.015	0.162	0.176
Reduced form	-4.635***	-5.576***	-0.012**	-0.026	-0.038*
First stage	0.541***	0.533***	0.533***	0.533***	0.533***
F-statistic	94.947	87.233	87.233	87.233	87.233
VtF 95% CV	1.918	1.916	1.919	1.922	1.922
Clusters (#)	1,743	1,743	1,744	1,744	1,744
Observations (#)	65,847,120	67,383,307	67,385,108	67,385,108	67,385,108
Unique patient-months in:					
Event counties (#)	78,797	80,271	80,271	80,271	80,271
Comp. counties (#)	5,867,165	5,988,933	5,989,062	5,989,062	5,989,062

	Stats/Pats At Chosen Center (6)	Nurs./Pats At Chosen Center (7)	1[Hosp.] (8)	1[URR <65%] (9)	Expected Utility (MTEs) (10)
1[Has Center]	0.105***	0.037***	-0.024*	-0.007	10.515***
	(0.021)	(0.006)	(0.013)	(0.027)	(0.884)
	[4.968]	[6.257]	[1.920]	[0.274]	[11.897]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	N	N	N	N	N
Comparison group	USA	USA	USA	USA	Reg.
Baseline *Y*	0.227	0.060	0.182	0.101	54.122
Reduced form	0.057***	0.019***	-0.013**	-0.003	6.008***
First stage	0.541***	0.500***	0.526***	0.446***	0.571***
F-statistic	94.948	43.530	79.544	30.706	83.364
VtF 95% CV	1.926	1.905	1.915	1.850	1.909
Clusters (#)	1,744	1,420	1,743	1,510	444
Observations (#)	65,849,229	33,349,406	54,686,614	34,143,755	8,453,182
Unique patient-months in:					
Event counties (#)	78,797	31,496	66,131	36,536	78,797
Comp. counties (#)	5,867,331	2,874,369	4,849,749	2,883,666	1,276,452

Tab. A9. *Sensitivity analysis of marginal centers' effects on patient access, health, and welfare.* This table reports the results of a robustness check of the IV-DID analysis. Unlike the main analysis, these estimates are computed without patient characteristics. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. Comparison groups are nationwide or regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussion near page 57. Source: author's analysis of the USRDS Database.

	Mi. to Chosen Center (1)	Mi. to Nearest Center (2)	1[HHD] (3)	1[PD] (4)	1[Home] (5)
1[Has Center]	-9.428***	-10.760***	-0.024**	-0.070**	-0.094***
	(1.465)	(1.586)	(0.009)	(0.034)	(0.033)
	[6.437]	[6.783]	[2.570]	[2.093]	[2.866]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	Reg.	Reg.	Reg.	Reg.	Reg.
Baseline *Y*	25.755	18.244	0.015	0.162	0.176
Reduced form	-5.376***	-6.035***	-0.013***	-0.039**	-0.053***
First stage	0.570***	0.561***	0.561***	0.561***	0.561***
F-statistic	84.257	76.984	76.984	76.984	76.984
VtF 95% CV	1.918	1.939	1.912	1.915	1.912
Clusters (#)	445	445	445	445	445
Observations (#)	8,497,491	8,605,362	8,605,362	8,605,362	8,605,362
Unique patient-months in:					
Event counties (#)	78,797	80,271	80,271	80,271	80,271
Comp. counties (#)	1,279,617	1,291,985	1,291,985	1,291,985	1,291,985
	Stats/Pats At Chosen Center (6)	**Nurs./Pats At Chosen Center (7)**	**1[Hosp.] (8)**	**1[URR <65%] (9)**	**Expected Utility (MTEs) (10)**
1[Has Center]	0.079***	0.033***	-0.018	-0.006	10.560***
	(0.019)	(0.006)	(0.012)	(0.024)	(0.853)
	[4.096]	[5.967]	[1.442]	[0.246]	[12.383]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	Reg.	Reg.	Reg.	Reg.	Reg.
Baseline *Y*	0.227	0.060	0.182	0.101	54.122
Reduced form	0.045***	0.017***	-0.010	-0.003	6.028***
First stage	0.570***	0.502***	0.556***	0.450***	0.571***
F-statistic	84.257	32.962	72.405	27.944	84.692
VtF 95% CV	1.926	1.868	1.911	1.838	1.910
Clusters (#)	445	391	442	403	444
Observations (#)	8,497,561	3,285,988	6,936,889	3,615,376	8,453,167
Unique patient-months in:					
Event counties (#)	78,797	31,496	66,131	36,536	78,797
Comp. counties (#)	1,279,622	719,041	1,043,137	682,411	1,276,451

Tab. A10. *Sensitivity analysis of marginal centers' effects on patient access, health, and welfare.* This table reports the results of a robustness check of the IV-DID analysis. Unlike the main results, these estimates are all computed using regional comparison groups. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussion near page 57. Source: author's analysis of the USRDS Database.

	Mi. to Chosen Center (1)	Mi. to Nearest Center (2)	1[HHD] (3)	1[PD] (4)	1[Home] (5)
1[Has Center]	-17.919***	-21.750***	-0.069*	-0.047	-0.117*
	(4.012)	(5.572)	(0.041)	(0.060)	(0.067)
	[4.466]	[3.904]	[1.682]	[0.787]	[1.742]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	USA
Baseline *Y*	37.649	26.704	0.035	0.151	0.186
Reduced form	-6.728***	-7.734***	-0.025*	-0.017	-0.042*
First stage	0.375***	0.356***	0.356***	0.356***	0.356***
F-statistic	14.322	12.560	12.560	12.560	12.560
VtF 95% CV	2.416	2.291	1.716	1.725	1.715
Clusters (#)	1,371	1,371	1,372	1,372	1,372
Observations (#)	35,145,628	35,966,063	35,967,155	35,967,155	35,967,155
Unique patient-months in:					
Event counties (#)	23,198	24,381	24,381	24,381	24,381
Comp. counties (#)	2,508,745	2,567,263	2,567,341	2,567,341	2,567,341

	Stats/Pats At Chosen Center (6)	Nurs./Pats At Chosen Center (7)	1[Hosp.] (8)	1[URR <65%] (9)	Expected Utility (MTEs) (10)
1[Has Center]	0.173***	0.056***	-0.071**	0.045*	17.982***
	(0.028)	(0.014)	(0.028)	(0.024)	(3.222)
	[6.082]	[4.139]	[2.527]	[1.898]	[5.581]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	Reg.
Baseline *Y*	0.227	0.067	0.161	0.073	85.502
Reduced form	0.065***	0.020***	-0.025***	0.015**	5.966***
First stage	0.375***	0.363***	0.349***	0.335***	0.332***
F-statistic	14.322	14.206	11.533	10.737	10.296
VtF 95% CV	2.341	1.976	1.726	1.685	2.587
Clusters (#)	1,372	1,369	1,367	1,364	211
Observations (#)	35,146,790	27,567,397	28,936,460	23,927,251	2,654,568
Unique patient-months in:					
Event counties (#)	23,198	18,729	20,426	17,141	23,198
Comp. counties (#)	2,508,828	1,967,762	2,065,431	1,707,865	187,955

Tab. A11. *Sensitivity analysis of marginal centers' effects on patient access, health, and welfare.* This table reports the results of a robustness check of the IV-DID analysis. Unlike the main results, these estimates are computed using only the 2007 WA reform. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. Comparison groups are nationwide or regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussion near page 57. Source: author's analysis of the USRDS Database.

	Mi. to Chosen Center (1)	Mi. to Nearest Center (2)	1[HHD] (3)	1[PD] (4)	1[Home] (5)
1[Has Center]	-6.396***	-7.741***	-0.012*	-0.055	-0.067
	(1.064)	(1.114)	(0.006)	(0.043)	(0.043)
	[6.012]	[6.950]	[1.819]	[1.280]	[1.563]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	USA
Baseline *Y*	20.734	14.497	0.005	0.167	0.172
Reduced form	-3.882***	-4.697***	-0.007*	-0.033	-0.040
First stage	0.607***	0.607***	0.607***	0.607***	0.607***
F-statistic	99.962	99.356	99.356	99.356	99.356
VtF 95% CV	1.937	1.953	1.924	1.924	1.924
Clusters (#)	1,728	1,728	1,729	1,729	1,729
Observations (#)	30,701,490	31,417,242	31,417,951	31,417,951	31,417,951
Unique patient-months in:					
Event counties (#)	55,599	55,890	55,890	55,890	55,890
Comp. counties (#)	5,836,053	5,957,675	5,957,804	5,957,804	5,957,804

	Stats/Pats At Chosen Center (6)	Nurs./Pats At Chosen Center (7)	1[Hosp.] (8)	1[URR <65%] (9)	Expected Utility (MTEs) (10)
1[Has Center]	0.088***	0.025***	-0.007	-0.034	10.014***
	(0.022)	(0.002)	(0.014)	(0.030)	(0.888)
	[4.066]	[15.792]	[0.484]	[1.123]	[11.273]
ZCTA and month FE	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y
Comparison group	USA	USA	USA	USA	Reg.
Baseline *Y*	0.226	0.051	0.192	0.127	53.294
Reduced form	0.054***	0.017***	-0.004	-0.018	6.652
First stage	0.607***	0.685***	0.601***	0.539***	0.664
F-statistic	99.963	166.009	87.535	22.924	106.407
VtF 95% CV	1.927	1.960	1.919	1.816	1.960
Clusters (#)	1,729	1,405	1,728	1,495	233
Observations (#)	30,702,437	5,781,992	25,750,152	10,216,501	5,798,599
Unique patient-months in:					
Event counties (#)	55,599	12,767	45,705	19,395	55,599
Comp. counties (#)	5,836,219	2,843,894	4,826,845	2,863,982	1,088,496

Tab. A12. *Sensitivity analysis of marginal centers' effects on patient access, health, and welfare.* This table reports the results of a robustness check of the IV-DID analysis. Unlike the main results, these estimates are computed using only the NC threshold-crossings. County-level cluster-robust standard errors in parenthesis and $|t|$ in square brackets. Baseline Y is the average value of the outcome in the event counties prior to their events. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include age, race, sex, ethnicity, primary diagnosis, payer, and dialysis start year controls. Comparison groups are nationwide or regional counties without centers on the events' effective dates. VtF critical values may be compared to $|t|$ to conduct weak instrument-robust inference at the 95% level. See the discussion near page 57. Source: author's analysis of the USRDS Database.

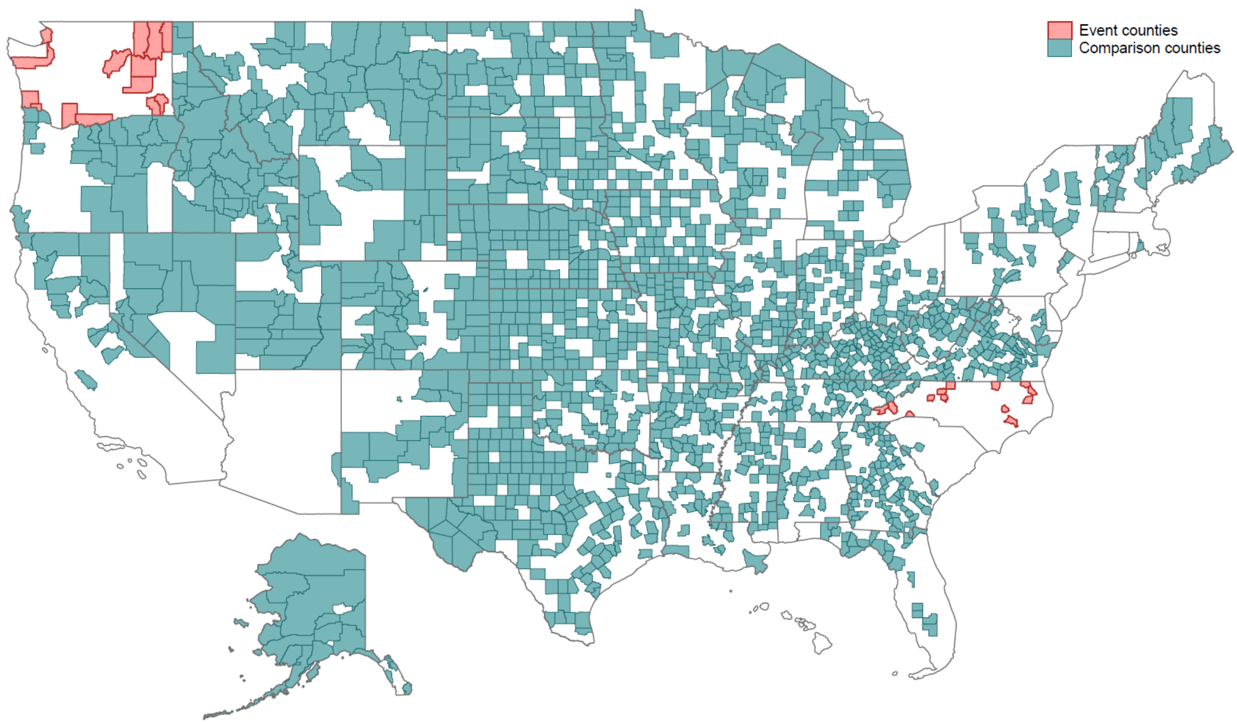
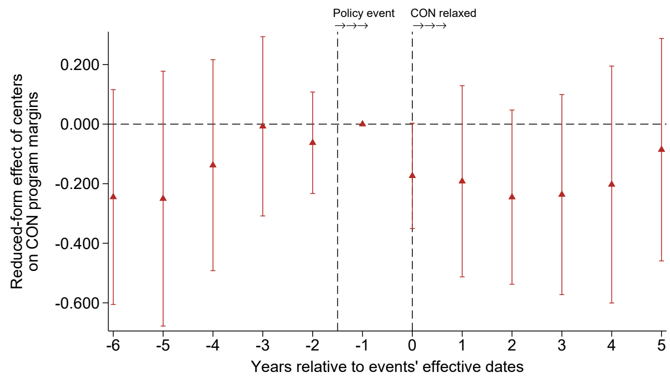
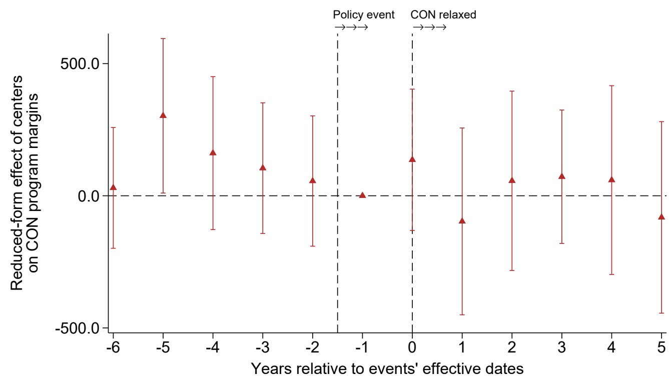


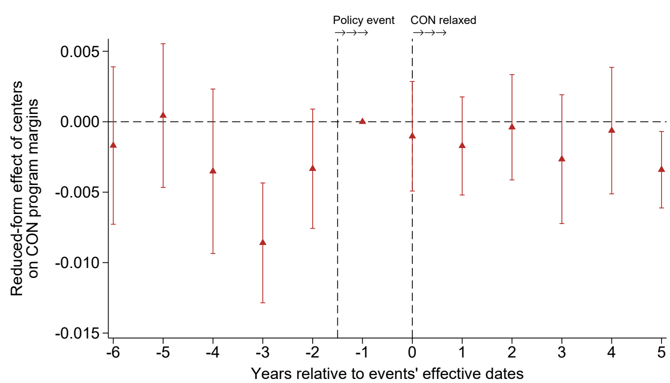
Fig. A1. *WA and NC event counties.* This map identifies the WA and NC counties where events statutorily relaxed CON-related entry barriers. It also identifies other counties in the U.S. that had zero centers at the time of one or more of the events, and that were consequently used in the comparison group of the IV-DID analysis. See the discussion near page 14. Source: author's analysis of the USRDS Database.



(a) HD sessions among HD patients



(b) Medicare spending among patients with Medicare FFS as a primary payer

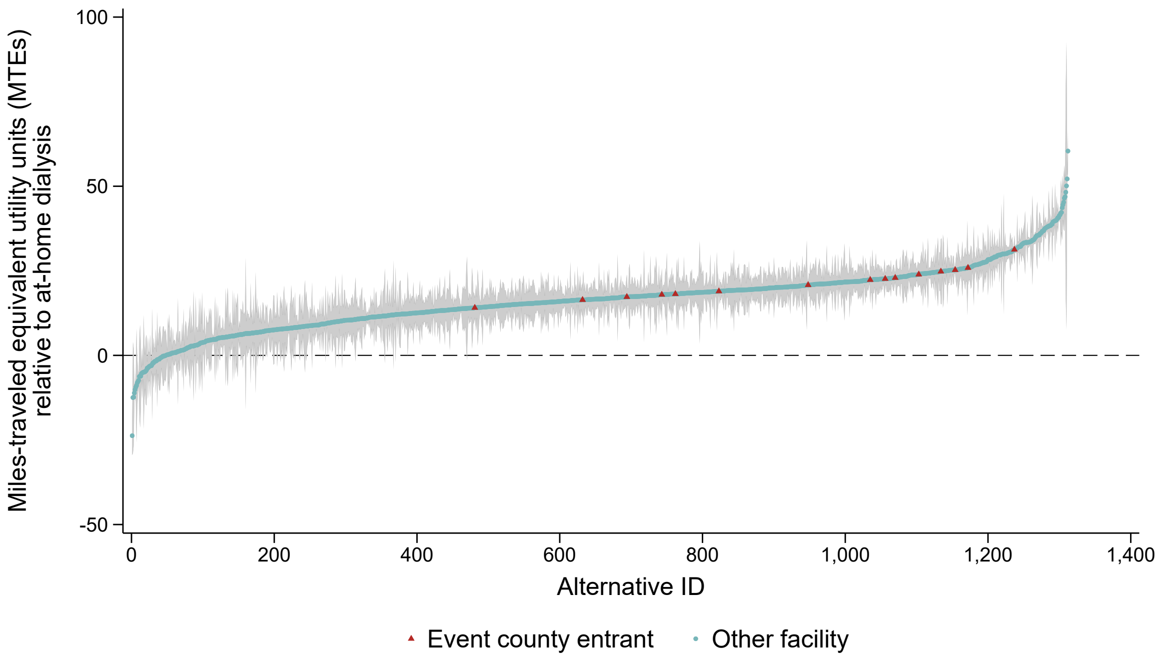


(c) 1[Died]

Fig. A2. *Reduced-form effect of WA and NC dialysis CON events on additional outcomes.* This figure plots results from the IV-DID analysis for additional outcomes. The bars are 95% confidence intervals computed with county-level cluster-robust standard errors. The dashed lines mark the events' actual and effective dates in relative time. Since the events could not cause centers to open instantaneously, I assume that their effective dates are 18 months later. See table A8 and the discussion near page 56. Source: author's analysis of the USRDS Database.

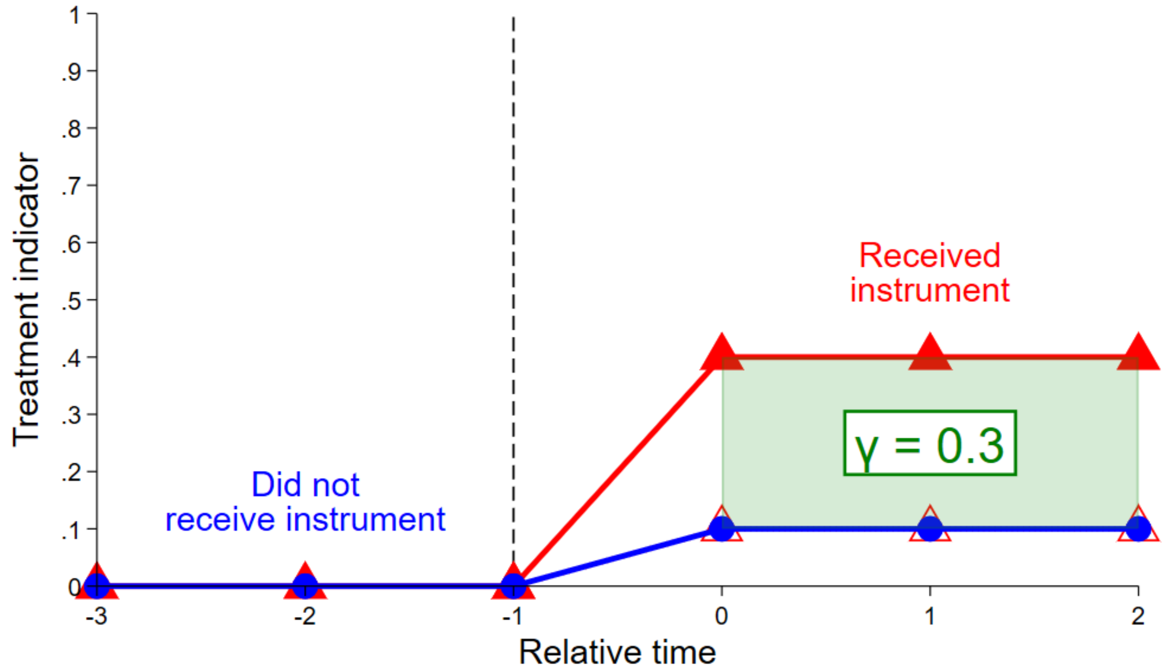
	(1)
TrDist	-0.129***
	(0.005)
TrDist^2	0.000***
	(0.000)
1[Stay]	5.878***
	(0.036)
Cases (#)	1,368,224
Alts. (#)	1,312
Observations (#)	27,881,747
Clusters (#)	447
Alts. per case:	
Avg. (#)	20
Min. (#)	2
Max. (#)	93

(a) Travel and switching cost estimates

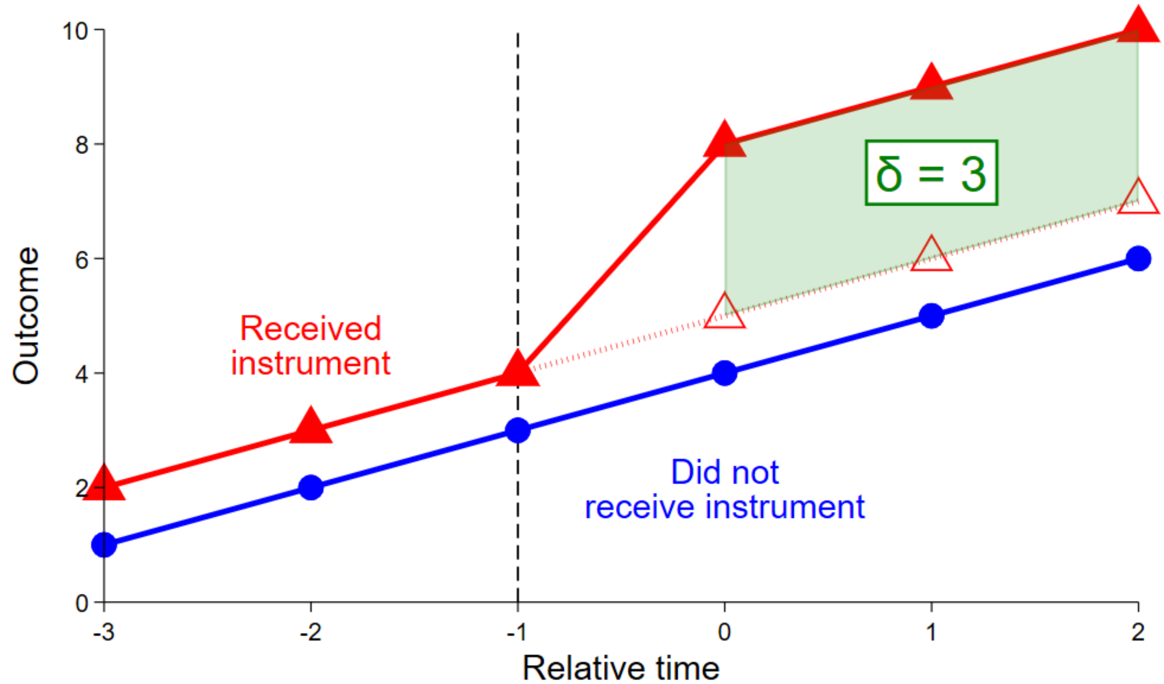


(b) Distribution of alternative-specific fixed effect estimates

Fig. A3. *Sensitivity analysis of estimates of treatment choice model.* Panel (a) reports estimates of γ_1, γ_2, and λ in equation (F.4). County-level cluster-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel (b) plots the distribution of alternative-specific fixed effects scaled by $-\hat{\gamma}_1$. Shaded areas are 95% confidence intervals. See the discussion near page 57. Source: author's analysis of the USRDS Database.



(a) First stage event study



(b) Reduced form event study

Fig. A4. *Illustration of IV-DID identification strategy.* This figure presents the IV-DID identification strategy in a stylized example. Under the assumptions discussed near page 55, the ratio δ/γ identifies the CATE-ES. Source: author's illustration.