Entry Barriers in Provider Markets: Evidence from Dialysis Certificate-of-need Programs

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Abstract. Can entry barriers in health care provider markets raise welfare? In the U.S., proponents of regulatory entry barriers called CON programs claim that they reduce waste by limiting "unnecessary" entry. I examine CON programs in the dialysis industry, where their effects on market structure, access, health, costs, and welfare are poorly understood, and where patients are sensitive to access and quality. I combine quasi-experimental policy variation in low population areas with a structural model of patient preferences to find that marginal entrants improved access significantly, reduced hospitalization rates, and generated for patients the utility value of traveling 275-344 fewer miles per month; but there is evidence that they contributed even more to fixed costs. Using policy variation throughout North Carolina, I also find evidence that the NC dialysis CON program created a mechanism through which incumbents could block potential entrants by expanding in tandem with their local patient populations. Taken together, my findings suggest that stronger regulatory entry barriers in low population areas may raise total welfare at patients' expense—but they also amplify concerns that CON programs dampen competition statewide.

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Health care expenditures in the United States are high and rising, continuing a decades-long trend. Concerns about health care expenditures in the 1960s-70s spurred lawmakers to establish certificate-of-need programs ("CON programs," hereafter) to regulate entry and capacity investments in health care provider markets (Salkever, 2000). Still widely used, they are now one of the country's oldest health care cost-containment measures. In states with CON programs, hospitals, nursing homes, dialysis centers, and other health care providers seeking to open new facilities or expand existing capacity must apply for permission from their state's health planning agency. If the agency finds that an investment is "unnecessary," then the agency may block it by withholding a certificate of need. In this study, I examine whether regulatory entry barriers like CON programs influence market structure, treatment access, patient health, costs, and, ultimately, welfare.

Proponents of CON programs argue that they raise welfare by reducing waste. The theory goes that moral hazard, provider-induced demand, business-stealing, and retrospective, cost-based payment systems create an environment where unregulated providers may overinvest in health care resources and pass the costs of their overinvestments onto patients and insurance subscribers. For instance, the moral hazard and provider-induced demand theories suggest that health care resources may be overutilized (e.g., Roemer, 1961; Arrow, 1963). If treatments provided by the marginal unit of capacity reduce welfare, then the social value of the marginal unit of capacity may itself be negative. The business-stealing theory suggests that a provider's investments may cause her to treat patients who might have otherwise been treated by a competitor. Health care providers who fail to internalize such negative externalities may overinvest (e.g., Mankiw and Whinston, 1986; Gaynor, 2006). Proponents of CON programs argue that if states could determine when and where health care resources are "needed," then they could reduce waste by prohibiting unnecessary expenditures.

Detractors of CON programs argue that they reduce welfare by limiting valuable competition and reducing treatment access. If CON programs misclassify some capital investments as "unnecessary" by adopting excessively restrictive policies, then there may be too few health care providers or too little capacity. Consequently, health care providers may feel less competitive pressure to raise quality or lower prices (e.g., Pauly, 2004; Gaynor and Town, 2012; Chandra et al., 2016)—or they may simply be too crowded to respond to demand fluctuations (Hoe, 2019)—and patients may have to travel farther, wait longer, or pay more for poorer health care.

In this study, I examine CON programs' entry limits in the U.S. dialysis industry. Dialysis is a life-saving treatment for end-stage renal disease ("ESRD," hereafter). Individuals with ESRD have little or no normal kidney function. They are typically older than the general population and have several other chronic conditions. Most dialysis patients are treated three times a week at specialized, for-profit medical facilities called dialysis centers that consist of dialysis stations

(i.e., units of equipment capable of treating one patient at a time), nurses, patient care technicians ("PCTs," hereafter), a renal dietician, and a medical doctor. Most dialysis centers are owned by a large national chain or a small local chain. Dialysis patients may also perform dialysis by themselves at home or at work, thereby reducing their travel costs but forgoing the direct assistance of dialysis centers' medical staff.

I focus on the dialysis industry for several reasons. First, dialysis patients are sensitive to treatment quality and access because of their relatively poor health and their persistent dependence on nonresidential medical facilities. Second, investments that improve dialysis patients' health may have significant returns in other health care market segments: although dialysis patients were approximately 1% of the Medicare fee-for-service (FFS) population in 2018, they accounted for approximately 7.2% of Medicare FFS spending in that year (USRDS, 2020). Third, dialysis itself is costly. Medicare expenditures for dialysis care in 2013 were about $31,100 per patient (U.S. GAO, 2015) and there are more than 100,000 incident cases of ESRD every year (USRDS, 2020). Fourth, dialysis CON programs are prevalent. Eleven states and Washington, D.C. had CON programs that regulated the supply of dialysis resources in 2016 (AHPA, 2016).

I estimate the effects of dialysis CON programs' entry limits by leveraging quasi-experimental within-county variation in their stringency. In doing so, I improve upon the existing literature with respect to identification by credibly linking market structure variation to dialysis CON programs. I use two similar but unrelated sources of variation. First, I leverage a 2007 policy change in Washington that relaxed the WA dialysis CON program's entry limits in counties without any dialysis centers (the "2007 WA policy change," hereafter). Second, I leverage threshold rules in North Carolina that relaxed the NC dialysis CON program's entry limits in counties without any dialysis centers when those counties' patient populations happened to cross a prespecified threshold (the "NC threshold-crossings," hereafter). Prior to these relaxations, both the WA and NC dialysis CON programs had been in principle less permissive of entry because the counties' patient populations were "too low" to justify a new dialysis center. I analyze these events using difference-in-differences methods to infer how the observed data differ from data that would have been generated had the WA and NC dialysis CON programs *not* relaxed their entry limits. While the 2007 WA policy change and the NC threshold-crossings may each individually generate enough variation to estimate the effects of dialysis CON programs' entry limits, I am able to infer which effects are more typical and which effects are less typical by leveraging both sources of variation.

My findings indicate that dialysis CON programs are important determinants of market structure, treatment access, and, in some contexts, patient health. First, I find that the WA and NC dialysis CON programs spurred entry when they relaxed their entry limits, suggesting that their entry limits

had been binding. Second, I find that the dialysis centers on the WA and NC dialysis CON programs' policy margins (the "marginal centers," hereafter) improved treatment access: patients had more nearby dialysis centers, received treatment at nearer centers, relied less on self-managed, at-home dialysis, and benefited from more health care resources at their chosen centers. The magnitude of these access benefits is striking. For instance, patients living in counties that experienced a dialysis center opening because their state's dialysis CON program relaxed its entry limits traveled 21 fewer miles (in WA) or 8 fewer miles (in NC) in each direction to and from their chosen dialysis center three times per week, on average.[1][2] Such changes may significantly benefit those older and sicker dialysis patients who make frequent trips to dialysis centers—sometimes in heavy rain and snow—or those who rely on a relative or friend to drive. Finally, I find that the marginal centers in Washington reduced the probability that a nearby patient experienced a hospitalization in a given month by approximately 6.9 percentage points. On aggregate, this was approximately 2.1 fewer hospitalizations per county-month. Most of these hospitalizations were associated with a cardiovascular-related event. However, I do not find evidence that the marginal centers significantly affected dialysis adequacy measures or mortality in either Washington or North Carolina.

Having estimated the effects of dialysis CON programs' entry limits on entry, treatment access, and patient health, I proceed to use these estimates to compute the marginal centers' total welfare contributions. I argue that institutional characteristics of the U.S. dialysis industry, clinical characteristics of dialysis treatments, and particularities of dialysis CON programs imply that other subjects sometimes raised by proponents and detractors of CON programs—such as overutilization and prices—are lesser concerns in this context. With respect to overutilization, dialysis CON programs take as given a community's dialysis patient population in order to determine the community's need for dialysis resources. Therefore, it is unclear how dialysis CON programs could curb overutilization (to the extent that it exists in this context at all). With respect to prices, individuals with ESRD are eligible for Medicare regardless of their age. Consequently, Medicare was the primary payer for about 80% of dialysis patient-months between 1980 and 2016. There is some evidence that commercial insurance prices for the remaining 20% of patient-months are much higher than Medicare prices.[3] While the extent of price competition in the U.S. dialysis industry

[1] I measure distances using straight-line miles between ZCTA centroids. All distances reported in this paper are straight-line miles, unless otherwise noted. For reference, Boscoe et al. (2012) estimated that the average detour index in the United States is approximately 1.417—that is, each straight-line mile is equivalent to approximately 1.417 driving miles.

[2] The nationwide average travel distance between patients and their chosen dialysis centers is about 8.8 miles. In WA counties affected by the 2007 WA policy change, the baseline average travel distance had been about 33 miles. In NC counties affected by the threshold-crossings, the baseline average travel distance had been about 19 miles.

[3] Trish et al. (2021) found evidence in 2016 claims data that commercial insurance payments were around 3 times higher than Medicare payments ($10,149 per month vs. $3,364 per month). Similarly, Childers et al. (2019) found evidence in DaVita's 2010-2017 annual financial statements that revenues from commercial insurance were around 4

is unknown—and beyond the scope of this paper—it is plausible that CON programs' effects on average prices are somewhat muted because of Medicare's relative prominence.

I estimate the marginal centers' total welfare contributions through their effects on treatment access, patient health, and fixed costs in three steps. First, I estimate patient preferences using a discrete choice model relating patients' distaste for travel to their tastes for dialysis center characteristics and at-home dialysis. I combine estimates from the discrete choice model with the foregoing sources of quasi-experimental variation to measure the marginal centers' contributions to patient welfare. Since I do not observe patients making dollar-valued transactions in this context, patient welfare is not identified in dollars. I therefore express patient welfare in miles-traveled equivalent utility units ("MTEs," hereafter). I find that patients' revealed preferences imply that each marginal center contributed to total patient welfare approximately 10,500 MTEs per month, on average.

Second, I collect fixed cost data filed by dialysis centers with Medicare and published by Medicare in the Healthcare Cost Report Information System ("HCRIS," hereafter). The data suggest that the marginal centers contributed to fixed costs approximately $35,000 per month (in NC) and $48,000 per month (in WA), on average.

Finally, I consider two missing ingredients. The first missing ingredient is the dollar value of an MTE. Let this be denoted by κ_1. The second missing ingredient is the marginal centers' contribution to welfare through their effect on hospitalization rates. Dialysis patients may not fully internalize the consequences of their treatment choices on their health outcomes or their health care resource utilization. Consequently, the foregoing patient welfare estimates may understate the benefits of dialysis center openings on the WA dialysis CON program's policy margins insofar as they understate the marginal centers' effects on nearby patients' hospitalization rates. However, the extent to which dialysis patients internalize these consequences is unknown. Let the omitted welfare benefit of one hospitalization be denoted by κ_2. In North Carolina, I find evidence that the dialysis centers on the NC dialysis CON program's policy margin increased total welfare in the short run if $10,500\text{MTE} \times \kappa_1 \geq \$35,000$. In Washington, I find evidence that the dialysis centers on the WA dialysis CON program's policy margin increased total welfare in the short run if $10,500\text{MTE} \times \kappa_1 + 2.1\text{hospitalizations} \times \kappa_2 \geq \$48,000$.

I benchmark these findings with proxies for (κ_1, κ_2). I synthesize information about hospitalization costs (Moore et al., 2014), vehicle operating costs (AAA, 2010), and a range of opportunity costs of time between $2 and $15 per hour. I find evidence that a plausible range for κ_1 is $1.20-$2.19. This suggests that the dialysis centers on the NC dialysis CON program's policy margin

times higher than revenues from public payers ($148,722 per year vs. $35,424 per year).

were unlikely to have increased total welfare in the short run. If $\kappa_1 = \$1.70$—the median of $[\$1.20, \$2.19]$—then my back-of-the-envelope calculations suggest that dialysis centers on the WA dialysis CON program's policy margin would have increased total welfare if $\kappa_2 \geq \$14,357$. By comparison, the average cost of a hospitalization for Medicare patients was approximately $12,000 in 2008 (Moore et al., 2014). These benchmarks illustrate that incrementally more stringent entry limits in low population WA and NC counties may sometimes raise total welfare. However, these total welfare gains would come at considerable expense to local patients.

The foregoing estimates are based on variation in dialysis CON programs' entry limits in counties without any dialysis centers—that is, counties with relatively low patient populations. However, dialysis CON programs may also influence market structure and welfare in a much larger region. I therefore supplement this work with an examination of the NC dialysis CON program's entry limits in counties with incumbents. I analyze 22 years of CON applications and the data underlying the NC dialysis CON program's determinations of where and when new centers were "needed." I find that providers that seek to open a new dialysis center in a NC county with an incumbent and that are not affiliated with that incumbent ("outsiders," hereafter) face a significant regulatory entry barrier; however, incumbents that seek to open a new dialysis center by spinning off part of their existing stock of dialysis stations to a new location appear to do so quite freely. Simultaneously, I find evidence that if an incumbent grows its centers' capacities at pace with its county's local patient population, then it could cause the NC dialysis CON program to never relax its entry limits for outsiders. These findings suggest that the NC dialysis CON program may be conferring market power upon incumbents by insulating them from potential competition. They raise concerns about potentially harmful statewide competitive effects.

While these findings are primarily informative of the effects of the WA and NC dialysis CON programs in low populations areas in Washington and North Carolina, they may also be informative of the effects of dialysis CON programs elsewhere and of CON programs more generally. First, the WA and NC dialysis CON programs' entry policies are broadly similar to other states' dialysis CON programs' entry policies. Since the 2007 WA policy change and the NC threshold-crossings are unrelated, that my estimates of the marginal centers' contributions to patient welfare in both Washington and North Carolina are similar suggests that centers on other dialysis CON programs' policy margins may also have similarly-sized effects. Second, competition authorities have long-claimed that CON programs in other health care market segments dampen competition by insulating incumbents from outsiders. My findings in North Carolina with respect to the NC dialysis CON programs' competitive effects are evidence in support of such claims.

This study relates to several strands of literature. First, it contributes to a small set of studies

that have previously examined dialysis CON programs (Ford and Kaserman, 1993; Dai, 2014; and Dai and Tang, 2015). This literature has measured differences between states with and without dialysis CON programs and found that states with dialysis CON programs tend to have fewer centers and less capacity than other states. Studying differences between states with and without dialysis CON programs is a useful exploratory exercise. However, it may be unreliable for the purposes of drawing inferences about the effects of dialysis CON programs because states with and without dialysis CON programs may differ in other ways. For instance, the geographic distribution of dialysis centers may depend not only on dialysis CON programs, but also on payments, costs, patients' geographic distribution, and patients' preferences. It is therefore unclear what differences between states with and without dialysis CON programs are attributable to dialysis CON programs themselves, and what differences are attributable to other factors. I overcome this identification problem by leveraging within-county variation directly attributable to the WA and NC dialysis CON programs.

Second, this study contributes to the health care economics literature concerned with CON programs more broadly. Other studies have examined CON programs vis-à-vis imaging technology (e.g., Horwitz and Polsky, 2015; Stratmann and Baker, 2016; Perry, 2017); home health services (e.g., Polsky et al, 2014); cardiac surgery (e.g., Vaughan-Sarrazin et al., 2002; Ho, 2004; Ho 2006; Popescu, Vaughan-Sarrazin, and Rosenthal, 2006; DiSesa et al. 2006; Cutler et al., 2010); and several other health care market segments. I contribute new evidence of of how CON programs affect market structure, treatment access, and patient health in the U.S. dialysis industry. I also describe a mechanism through which CON programs can insulate incumbents from potential competition.

Third, this study contributes to the industrial organization literature concerned with the externalities of firm entry. Mankiw and Whinston (1986), Gaynor (2006), and others in the theoretical literature showed that unregulated entry may lead to either an excessive or insufficient number of firms. Free entry may lead to an excessive number of firms if entrants exert negative externalities. For instance, they may exert so-called "business-stealing externalities," whereby they serve consumers that might otherwise have been served by a competitor. Or free entry may lead to an insufficient number of firms if entrants exert positive externalities. For instance, they may exert so-called "product variety externalities," whereby they make uncompensated improvements to consumers' access to a product variety. The theory predicts that regulatory entry scrutiny—like CON programs—may be justified for the purposes of maximizing total welfare if entrants' externalities are negative on net. Several empirical studies have examined the externalities of firm entry in a variety of industries (e.g., Berry and Waldfogel, 1999; Rysman, 2004; Davis, 2006; Gowrisankaran and Krainer, 2011; Seim and Waldfogel, 2013). I contribute evidence from the U.S. dialysis industry

of a regulator charged with cuttings costs associated with "unnecessary" entry.

Finally, this study contributes to the growing industrial organization literature concerned with the U.S. dialysis industry. This literature has found evidence of a quality-quantity trade off in the production of dialysis treatments (Grieco and McDevitt, 2017); evidence that a center's chain affiliation is an important determinant of treatment quality and operations (Wilson, 2016a; Eliason et al., 2020a); evidence that a patient's proximity to nearby dialysis centers is an important determinant of where they are treated (Eliason, 2021); evidence that quality competition responds to the geographic distribution of dialysis centers (Eliason, 2021); mixed evidence that quality competition responds to acquisitions (Wilson, 2016b; Wollmann, 2020; and Eliason et al., 2020a); evidence that existing centers can make entry by subsequent centers less likely (Dai, 2014 and Dai and Tang, 2015); and evidence that Medicare is an important determinant of entry (Eliason, 2021; and Dai and Tang, 2015) and clinical practices (Eliason et al., 2020b). I contribute evidence that dialysis CON programs are also important determinants of market structure and patient outcomes.

The remainder of this paper proceeds as follows. In section I.A, I describe dialysis, the U.S. dialysis industry, and my data. In section I.B, I discuss the economics of CON programs. In section II, I report differences between states with and without dialysis CON programs. In section III, I measure the effects of the WA and NC dialysis CON programs' entry limits on entry, patient welfare, and fixed costs in counties without incumbents. In section IV, I discuss how the NC dialysis CON program's entry limits affect competition in counties with incumbents. In section V, I conclude.

I. Background

A. Dialysis and Data

Dialysis is the primary treatment for ESRD. Individuals with ESRD have virtually no kidney function. As a result, they are unable to independently filter wastes that naturally accumulate in their blood. ESRD may be treated with a kidney transplant or dialysis, but most individuals with ESRD rely on dialysis because donor kidneys are scarce. While some patients pay for dialysis with commercial insurance, Medicare was the primary payer for most dialysis patient-months between 1980 and 2016.[4] Dialysis centers are the primary clinical settings for dialysis treatments.

[4]Medicare coverage is extended to a person of any age with ESRD. If an individual is enrolled in an employer-sponsored group health plan at the time that they are diagnosed with ESRD, then Medicare acts as a secondary payer for 30-33 months before taking over as the primary payer. There is evidence that commercial insurance pays more than

There are two kinds of dialysis ("modalities," hereafter). Hemodialysis is the most common dialysis modality ("HD," hereafter). During a typical HD session, patients are intravenously connected to an artificial kidney machine. The machine siphons blood out of their body, pumps it through a filter, and then siphons it back into their body. This process usually takes 3-5 hours. Most HD patients receive thrice weekly treatments at a dialysis center, but a very small number receive at-home hemodialysis ("HHD," hereafter). Peritoneal dialysis is the second most common dialysis modality ("PD," hereafter). During a typical PD session, dialysate rests inside a patient's peritoneal cavity and cleans blood that naturally circulates through the area. The dialysate is refreshed throughout the day (or night) through a catheter surgically placed in their abdomen.[5] PD treatments occur daily. HHD and PD patients usually become affiliated with a dialysis center for training, support, and supplies, but do not travel there thrice weekly for treatment. I refer to HHD and PD collectively as "at-home dialysis." At-home dialysis patients benefit from lower travel costs. In the case, of PD, they may also experience "[g]reater lifestyle flexibility and independence" and "longer lasting residual kidney function" (Mayo Clinic: Peritoneal Dialysis). However, at-home dialysis patients do not have the direct assistance of dialysis centers' medical staff.

I construct the patient data used in this study from records supplied by the U.S. Renal Data System ("USRDS," hereafter). The USRDS is a "national data system that collects, analyzes, and distributes information about chronic kidney disease (CKD) and end-stage renal disease (ESRD) in the United States." (USRDS, 2021). It aggregates, organizes, and distributes data from CMS, the United Network for Organ Sharing, and other sources for research purposes. The data have been described in detail elsewhere. (See, e.g., Eliason, 2021; Eliason et al., 2020a; Eliason et al., 2020b; and Wollmann, 2020.) The USRDS also publishes detailed guides that describe its process for aggregating and organizing these data (e.g., USRDS, 2020).

The patient data used in this study consist of patient-months spanning 1980-2016. For each patient, I observe demographic information (including age, race, ethnicity, and sex), their primary cause of kidney disease (such as diabetes, hypertension, or glomerulonephritis), and whether they were working full time, part time, or neither at the time of their diagnosis. For each patient-month, I observe a residence at the ZIP code level, a modality, an indicator for whether the patient has a kidney transplant, their primary dialysis center, and an indicator of whether they have Medicare

Medicare. See footnote 3. Before 1983, Medicare paid dialysis centers with a fee-for-service payment scheme. From 1983-2011, Medicare paid dialysis centers with a fixed per-treatment fee and a separate fee for certain drugs. Since 2011, these fees have been bundled together into a single per-treatment fee. See Swaminathan et al. (2012) for an interesting history of the Medicare ESRD payment system.

[5]The need for a catheter raises the costs of switching into PD. I observe approximately 1.7 million patients who used in-center HD for the first twelve months of their treatment. Approximately 50,000 of these patients (or 3%) subsequently switched into PD. On the other hand, I observe only approximately 130,000 patients who used PD for the first twelve months of their treatment. Approximately half subsequently switched into in-center HD.

or commercial insurance. I also observe for each patient a death date, if they died on or before 2016. I observe each patient's hospital and dialysis center claims while Medicare was their primary payer. I use the ICD-9 codes included in the claims data to identify hospitalizations associated with cardiovascular events or infections.[6] I also use the claims data to identify the number of HD-equivalent dialysis treatments a patient received in each month. Finally, since 1998, I observe Medicare patients' urea reduction ratios ("URRs," hereafter). A URR of at least 65% is considered a sign of adequate dialysis (NIDDK, 2021).

I construct the dialysis center data used in this study from records supplied by the USRDS and HCRIS. The USRDS data span 1980-2016 and originate from the CMS Annual Facility Survey. For each center-year, I observe a ZIP code-level location; a chain affiliation; a number of nurses, PCTs, and renal dieticians (since 2004); and a stock of dialysis stations. I supplement these data with annual cost data reported by dialysis centers to Medicare and published by Medicare in HCRIS from 2011 to 2016. The HCRIS data contain several cost categories, including "depreciation on buildings and fixtures and expenses [...] such as insurance, interest, rent, and real estate taxes," "depreciation on movable equipment and expenses [...] such as insurance, interest, personal property taxes, and rent," and "direct expenses incurred in the operation and maintenance of the plant and equipment and protecting employees, visitors, and facility property" including "maintenance and service of utility systems, such as heat, light, water [...], air condition, and air treatment." I combine these cost categories into a measure of fixed costs.

I construct the geographic data used in this study from several sources. First, I link the foregoing patient and dialysis center data to the UDS Mapper's ZIP-to-ZCTA crosswalk. UDS Mapper is an online data clearinghouse associated with CMS and several other health care and health care research organizations. Then, I link the patients and dialysis centers' ZCTAs to one another to construct geographic distances using the National Bureau of Economic Research's ZCTA distances database. The geographic distance data are straight-line distances between ZCTA centroids, unless otherwise noted. Finally, I construct a measure of each county's rurality using the U.S. Census Bureau's enumeration of county-level rural populations.

Table 1 presents several descriptive statistics about dialysis patients between 1980 and 2016. They are mostly white (54%), black (28%), and male (55%). At the time of their diagnosis, a minority had full-time employment (17%); and their doctors attributed their kidney disease primarily to diabetes (49%) and hypertension (33%). They were 168 centimeters tall (5.5 feet) and weighed 80 kilograms (176 pounds), on average. Diabetes, high blood pressure, cardiovascular disease, smoking, obesity, and abnormal kidney structure are risk factors for ESRD. Most dialysis

[6] I categorize ICD-9 codes into these groups as in Zhang et al. (2019).

patients never receive a transplant (87%). In any given month, most patients traveled to a dialysis center for thrice-weekly HD treatments (89%). The rest used HHD (1%) or PD (10%). They were 62 years old and they were affiliated with dialysis centers 8.8 miles away, on average. The average patient's dialysis center treated 104 patients, had 21 stations, 7 nurses, 9 PCTs, and 1 renal dietician. Eighty percent of patients used Medicare as their primary payer. Fourteen percent of Medicare patients experienced a hospitalization. Thirteen percent of Medicare patients experienced a hospitalization associated with a cardiovascular event, and six percent experienced a hospitalization associated with an infection. On average, Medicare patients received 11.7 HD-equivalent dialysis sessions, 18% received fewer than 12, and most patients had an adequate URR (87%).

Table 2 reports several descriptive statistics about dialysis centers between 1980 and 2016.[7] In any given year, dialysis centers have seventeen dialysis stations on average. Some provide at-home training and support services to at least one HHD patient (16%) and at least one PD patient (44%). They staff five nurses, six PCTs, and one renal dietician, on average. The nurses and PCTs perform most of the routine patient care. PCTs are sometimes high school graduates with in-house training, whereas nurses are licensed graduates from accredited schools of nursing. Dialysis centers are operated independently (10%), by a small local chain (27%), or, most commonly, by one of two for-profit national chains: DaVita (28%) and Fresenius (35%). Finally, dialysis centers treat 70 patients on average.

Finally, I rely on data from the NC dialysis CON program published in semiannual dialysis reports ("SDRs," hereafter) between 1997 and 2019. The data contain the NC dialysis CON program's own records of each NC county's patient population and each NC dialysis center's stock of dialysis stations and patient volume. The NC dialysis CON program used these data to determine when and where additional dialysis resources were needed. I also rely on a database of applications for certificates of need. The applications were filed for permission to begin various capital projects, including entries. For each project, the data contain the date that the application was filed, the county where the proposed dialysis center would be located, a narrative description of the project, and an indicator for whether the application was approved.

B. The Economics of CON Programs

CON programs have regulated dialysis centers and other health care providers—including hospitals, nursing homes, and home health services—since the 1960s. At that time, policymakers

[7] Staffing variables are available for only 2004-2016.

and the public were intensely concerned about overinvestment in health care provider markets, possibly because of a perception that the costs of overinvestment were borne by taxpayers and insurance subscribers. Salkever (2000) attributed some of these concerns to the 1965 introduction of Medicare and Medicaid, which were seen as publicly funded, cost-based reimbursement systems that "paid hospitals in a manner that provided virtually no efficiency incentives." Firsthand accounts by lawmakers involved in the establishment of CON programs support this view. For instance, in his June 6, 1974 address to the IL State Senate advocating for the bill that would create the IL CON program, State Senator Jack Knuepfer stated that "We all pay for [the] surplus in hospital facilities[.] [...] [E]ither the Federal Government, the State Government, or your insurers pay [the] bill." (Knuepfer, 1974). Likewise, Lanning, Morrisey, and Ohsfeldt (1991) found evidence that higher per capita Medicaid expenditures predicted the adoption of CON programs.

CON programs distinguish between necessary and unnecessary capital projects using measures of "community need." For instance, the North Carolina dialysis CON program calculates how many stations operating at 3.2 patients-per-station are needed to serve six month projections of its counties' resident in-center dialysis patient populations. If a CON program finds that there is "no need" for a capital project, then it may block the project by withholding a certificate of need. In doing so, the hope is that CON programs reduce waste, raise treatment quality, and improve treatment access.

Waste could arise in unregulated health care provider markets due to provider-induced demand, moral hazard, and business-stealing effects. The provider-induced demand theory suggests that some providers with excess capacity are motivated by financial considerations to encourage their patients to receive high cost, low benefit treatments.[8] Moral hazard magnifies or substitutes for provider-induced demand. The theory goes that insured patients are less inclined to resist proposals that they receive (unnecessary) care, or they themselves may demand it (Arrow, 1963). Either way, if some treatments provided by the marginal unit of capacity reduce welfare, then the social value of the marginal unit of capacity may itself be negative. Business-stealing effects may also contribute to wasteful spending. The theory goes that if a provider's capital investment causes them to treat patients who might have otherwise been treated by a competitor, then the investment harms the provider's competitors by reducing their output. Providers consequently overinvest because their investments' private net benefits exceed their investments' social net benefits (Mankiw and Whinston, 1986; Gaynor, 2006). Proponents of CON programs argue that in markets with significant provider-induced demand, moral hazard, and business-stealing effects, CON programs raise welfare by cutting costs associated with unnecessary capital projects and unnecessary care.[9]

[8]Concerns about provider-induced demand were at the "foundation" of CON programs (Salkever, 2000).

[9]Senator Knuepfer expressed concern about wasteful investments in his June 6, 1974 address:

Proponents of CON programs also argue that they raise welfare by improving treatment access and quality. With respect to treatment access, the theory goes that entrants make uncompensated contributions to patient welfare by reducing their travel costs. Consequently, the geographic distribution of health care resources that arises in unregulated provider markets may be more concentrated than the socially optimal geographic distribution. CON programs may therefore improve treatment access by restricting entry into relatively overserved areas. With respect to quality, the theory goes that in markets where there is a positive causal relationship between a provider's output and average quality, business-stealing externalities may lower average quality by spreading output too thinly over too many providers. For instance, there is evidence of a positive output-quality relationship in cardiac surgery (Gaynor, Seider, and Vogt, 2005; Gowrisankaran, Ho, and Town, 2006).[10] CON programs may therefore improve quality in markets with a positive output-quality relationship by funneling patients to fewer providers.

Detractors of CON programs argue instead that they reduce treatment access and dampen competition, and that these harms outweigh any reduction in waste. With respect to access, the theory goes that although CON programs can restrict entry into what they characterize as overserved areas, they cannot directly incentivize entry elsewhere because they "do not have the ability to [...] act affirmatively" (Blumstein and Sloan, 1978). Consequently, providers who wish to enter where CON programs prohibit entry but do not wish to enter elsewhere may choose not to enter at all. Regulatory mechanisms that both encourage entry in some areas and discourage it in others may better align providers' geographic distribution with the regulator's intent. With respect to competition, the theory goes that CON programs confer market power upon incumbents by insulating them from potential competition. If incumbents exercise their market power, then

> "[The bill] addresses itself to a problem that we have in Illinois, and that problem is essentially a **surplus in hospital facilities**. [...] There are presently plans in the State of Illinois for almost 61 million dollars worth of new hospitals. In Springfield alone there are plans for two additional hospitals and it is somewhat doubtful if there are any hospitals...any additional hospitals needed, since **the present hospitals are not nearly full to capacity**. When a hospital is not full to capacity it costs more per bed for the rest of the patients. [...]
>
> "In my business, if I over expand, nobody buys...I have to charge too much. Nobody buys my product and I go out of business. That is not what happens to a hospital. [...] When you go to the hospital or I go to the hospital those 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 no one cares or the user cares not what it costs and does not and will not fight a cost increase.** [...]
>
> "Frequently hospital boards tend to get into competition with one another. Everyone wants the latest Cardiac Care Unit. Everyone wants the latest respiratory unit, and **they may not all be needed.**" [Knuepfer, 1974. Emphasis added.]

[10] Vaughan-Sarrazin et al. (2002) found that among Medicare patients who underwent coronary artery bypass graft ("CABG," hereafter) surgery in 1994-1999, "risk-adjusted mortality was [...] higher in [...] states that had no certificate of need regulation for open heart surgery than in [...] states [...] that had continuous certificate of need regulations" during that time.

they may reduce quality or raise prices.[11] There is some evidence that incumbents put additional pressure on policymakers to create CON programs in the 1960s-70s. For instance, Senator Knuepfer noted in his June 6, 1974 address that existing hospitals "have come to us asking to be put under this regulation."[12] Wendling and Werner (1980) found that higher hospital industry concentration predicted CON programs between 1968 and 1973, arguing that hospital industry concentration could lower "the costs of establishing a coalition to seek regulation."

Despite decades of disagreement, quasi-experimental evidence of CON programs' effects is scarce. Recently, several studies have attempted to bridge this gap in the literature. For instance, Cutler et al. (2010) used variation generated by the repeal of the PA CABG CON program; Perry (2017) used variation generated by threshold rules in the NC magnetic resonance imaging ("MRI," hereafter) CON program; and Polsky et al. (2014) used spatial variation within hospital referral regions that cross state boundaries. Each study found evidence that the CABG, home health, and MRI CON programs were binding on entry into their respective markets. However, their other findings were mixed.[13]

I contribute to this literature quasi-experimental evidence from the U.S. dialysis industry. Studying CON programs in several health care market segments—including dialysis—is worthwhile because the economic forces underlying CON programs' welfare effects vary in significance across health care market segments. For instance, dialysis CON programs seem unlikely to meaningfully cut costs arising from overutilization. There are at least two reasons. First, provider-induced demand and moral hazard seem unlikely to cause relatively healthy individuals to start receiving dialysis treatments.[14] Second, while relatively sick patients may overutilize dialysis along other

[11] Former FTC Commissioner Maureen Ohlhausen argued that CON programs "displace free market competition with regulation and tend to help incumbent firms amass or defend dominant market positions." (Ohlhausen, 2015). Similarly, the U.S. Department of Justice and Federal Trade Commission have said that CON programs "pose serious anticompetitive risks that usually outweigh their purported economic benefits." (Department of Justice and Federal Trade Commission, 2004).

[12] According to Senator Knuepfer, hospitals supported the legislation because "they [were] not in competition for your dollar" but "[t]hey want[ed] to be[.]"

[13] Cutler et al. (2010) found evidence that patient outcomes improved after the PA CABG CON program ended, primarily because hospitals began using more expensive, higher quality surgeons; but these welfare gains were approximately offset by entry costs. Perry (2017) found evidence that the NC MRI CON program reduced MRI utilization rates—thereby reducing health care expenditures—but health outcomes did not consequently deteriorate. Polsky et al. (2014) found "little or weak" evidence that home health CON programs worsened patient outcomes; but also that they had no detectable effect on expenditures.

[14] The provider-induced demand theory suggests that providers' scope for providing unnecessary treatments is greatest in clinical "gray areas," where the expected harm to patients of overutilization is low and uncertainty is high. For instance, studies have shown that the quantity of medical imaging is particularly sensitive to providers' reimbursement rates (Lee and Levy, 2012; Clemens and Gottlieb, 2014). Dialysis does not seem to fit this characterization well. Clemens and Gottlieb (2014) found that the quantity of dialysis treatments did not significantly respond to variation in Medicare reimbursement rates. Moreover, it seems unlikely that healthy individuals would seek out dialysis even if it were inexpensive because it is often time-consuming, uncomfortable, and exhausting.

margins—in theory, individuals with advancing kidney disease could start dialysis "too early," dialysis patients could forgo kidney transplants, or dialysis patients could overutilize in-center dialysis relative to at-home dialysis—dialysis CON programs' designs seem unlikely to significantly reduce overutilization along such margins because they commonly take the number of in-center dialysis patients as given and condition certain capital investments on whether centers meet *minimum* in-center utilization rate thresholds.[15][16] Likewise, dialysis CON programs seem unlikely to significantly reduce average prices because Medicare is the primary payer for most dialysis patient-months. On the other hand, dialysis CON programs may significantly affect patient welfare through their effects on treatment access. Since most dialysis patients travel to and from a dialysis center three times per week, the effects on patient travel of small changes to dialysis centers' geographic distribution can accumulate quickly.[17] A lack of access to dialysis centers can also cause patients to rely more on at-home dialysis. While at-home dialysis is clinically superior for some patients—such as those who can care for themselves—it may be inferior for patients who choose at-home dialysis because they have poor choice sets. Finally, dialysis CON programs might also affect patient health through quality competition (Eliason, 2021) or congestion (Grieco and McDevitt, 2016; Eliason, 2021), and they may affect fixed costs by reducing providers' expenditures on new treatment facilities. I therefore study dialysis CON programs' welfare effects by examining their effects on treatment access, patient health, and fixed costs.

II. Cross-sectional Evidence

I begin by re-examining differences between states with and without dialysis CON programs. This exercise is descriptive. It also serves to highlight the identification challenge that I aim to

[15]There is evidence that for-profit dialysis centers put patients on the transplant waitlist less frequently (Eliason et al., 2020a). However, the aggregate welfare effects of this behavior may be small because there are many more patients on the transplant waitlist than there are available kidneys. According to the USRDS, only 40% of individuals who were added to the transplant waitlist at any time between 2009-2013 received a kidney transplant within five years (USRDS, 2020).

[16]There is evidence that at-home dialysis is cheaper than in-center dialysis (U.S. GAO, 2015). Since patients are unlikely to internalize these cost differences—and since dialysis centers had financial incentives to persuade their patients to use in-center dialysis until 2011 (Eliason et al., 2020b)—it is conceivable that in-center dialysis is sometimes overutilized relative to at-home dialysis. U.S. GAO (2015) suggested that the availability of in-center dialysis capacity may have been a contributing factor to a decline in at-home dialysis utilization between 1988 and 2008.

[17]In Washington, patients have opportunities to file testimonials with the WA dialysis CON program to support a provider's application for a certificate of need. In testimonials filed in support of applications to open a county's first dialysis center, patients described that frequently making long trips—sometimes in poor weather—was uncomfortable and stressful. For instance, one patient wrote that she is "gone from home 6 hours," and that since her "husband can see very little and is hard of hearing," she "worr[ies] when [she] is not with him." Another wrote that she "does not leave town if there is any question of bad weather," but since the recent onset of her husband's ESRD, she "dread[s] this winter" because the couple will drive a long way for his treatment.

overcome below. In samples covering the 1980s (Ford and Kaserman, 1993) and 2007 (Dai, 2014; Dai and Tang, 2015), existing studies have documented that states with dialysis CON programs have fewer centers and fewer stations than states without dialysis CON programs.[18] Likewise, I compare Alabama, Alaska, Hawaii, Illinois, Maine, Mississippi, New York, North Carolina, Vermont, Washington, and West Virginia (the "dialysis CON states," in this section) to the other states between 2005 and 2016.[19]

I estimate linear regressions of the form

$$Y_{it} = \beta \mathbb{1}[\text{CON}]_{it} + \Gamma X_{it} + \text{FE}_t + \varepsilon_{it} \tag{1}$$

where (i, t) is a county-year, facility-year, or patient-month; Y_{it} is an outcome; X_{it} is a vector of county characteristics (including each county's number of dialysis patients and a measure of county rurality) and patient characteristics (including each patient's insurance status, age, race, sex, ethnicity, and cause of ESRD); and FE_t is a period fixed effect.

First, I analyze a sample of county-years. Table 3 reports that on average, while counties in the dialysis CON states were approximately 12.6 percentage points more likely to have a dialysis center (baseline [in the other states]: 54.7%), counties with at least one dialysis center had 0.478 fewer dialysis centers (baseline: 3.500) and 5.105 fewer dialysis stations (baseline: 58.208). On average, there were 0.251 fewer dialysis centers per county in the dialysis CON states (baseline 1.983), but no statistically significant difference in the number of dialysis stations. Table 4 reports that there were also no statistically significant differences in the number of nurses-per-resident-patient, dieticians-per-resident-patient, or PCTs-per-resident-patient in counties with or without at least one dialysis center.

Second, I re-estimated equation (1) using a sample of center-year observations. Table 5 reports that on average, dialysis centers in dialysis CON states treated 13.921 more patients per month, including 11.689 more in-center dialysis patients and 2.318 more at-home dialysis patients (baselines: 65.114, 59.523, and 6.701, respectively). This corresponds to an average of 0.058 fewer stations-per-patient (baseline: 0.326). There were no statistically significant differences in dialysis centers' nurses-per-patient, dieticians-per-patient, or PCTs-per-patient between the dialysis CON

[18] Ford and Kaserman (1993) regressed outcomes on an indicator for whether a particular state had a dialysis CON program in a particular year. Dai (2014) and Dai and Tang (2015) estimated structural entry models that included indicators for whether a state had a dialysis CON program as a control variable in the potential entrants' profit functions.

[19] The American Health Planning Association ("AHPA," hereafter) identified the CON states as having dialysis CON programs in both 2005 and 2016. It is difficult to construct a complete record of states with and without dialysis CON programs between 1980 and 2004 because many states repealed their dialysis CON programs before digitizing their laws or agency rules.

states and the other states. Table 6 reports that centers in dialysis CON states were slightly farther from their nearest competitors than centers in other states on average, though most estimates are not statistically significant.

Finally, I re-estimated equation (1) using a sample of patient-month observations. Table 7 reports that on average, patients in dialysis CON states were treated at centers with 0.028 fewer stations-per-patient (baseline: 0.254) and 0.001 fewer dieticians per patient (baseline: 0.012); but there was no statistically significant difference in the centers' nurses-per-patient or PCTs-per-patient. Table 8 reports that on average, patients in dialysis CON states did not live significantly farther from their nearest dialysis center or from their chosen dialysis center. However, they lived significantly farther from dialysis centers on the "less crowded" side of the national distribution of stations-per-patient. Table 9 reports that on average, patients in CON states were not significantly more likely to choose at-home dialysis. Table 10 reports that they were 0.6 percentage points less likely to experience a hospitalization in any given month (baseline: 13.5%), 0.6 percentage points less likely to experience a hospitalization associated with a cardiovascular event (baseline: 13.2%), and 0.4 percentage points less likely to experience a hospitalization associated with an infection (baseline: 6.5%). Table 11 reports that they were 1.5 percentage points less likely to experience fewer than 12 HD-equivalent sessions in a given month (baseline: 18.4%), but table 12 reports that they were not differentially more likely to experience a URR below 65%.

Taken together, these estimates imply that market structure and patient outcomes differ between dialysis CON states and other states. However, it is difficult to draw causal inferences from these differences. In theory, dialysis centers' entry decisions depend not only on CON programs, but also on costs, demand, and payments, which themselves depend on things like the local labor markets for medical professionals, the geographic distribution of dialysis patients, their preferences, their insurance status, their baseline health, and interactions thereof. Therefore, it is difficult to distinguish differences that are attributable to dialysis CON programs from differences that are attributable to other factors. I overcome this identification problem by leveraging within-county policy variation directly attributable to the WA and NC dialysis CON programs.

III. Evidence From Two Natural Experiments

I begin by describing the institutional context that gave rise to the policy variation. The WA and NC dialysis CON programs use two similar "need determination methodologies" to determine whether a given community needs a new dialysis center. They divide Washington and North Carolina into geographic planning areas that consist of groups of ZIP codes, a single county, or groups of

counties. They regularly collect data characterizing each planning area's dialysis patient population, project each planning area's dialysis patient population to some future date, apply a simple formula to calculate how many stations are needed to serve each planning area's projected dialysis patient population, and difference out each planning area's stock of existing dialysis stations. Applications to open new centers must satisfy such needs for additional dialysis stations.

In 2007, the WA dialysis CON program made two key changes to its need determination methodology in planning areas that had zero dialysis centers at the end of 2006. First, before 2007, the WA dialysis CON program measured each planning area's need for dialysis stations as that number of dialysis stations operating at 4.8 patients-per-station necessary to treat a 3-year projection of its resident in-center dialysis patient population, net of its stock of existing stations.[20][21] After 2007, the formula used 3.2 patients-per-station instead of 4.8 patients-per-station in the planning areas that had zero dialysis centers at the end of 2006.[22] Second, after 2007, providers seeking to open a new dialysis center in a given planning area could add an adjacent planning area's need for dialysis stations to their application if the adjacent planning area did not have a dialysis center. Many of the planning areas that had zero dialysis centers at the end of 2006 were adjacent to one another.[23] The 2007 WA policy change therefore made the WA dialysis CON program more permissive of entry in planning areas that had zero dialysis centers at the end of 2006.

In North Carolina, the NC dialysis CON program uses a simple threshold rule to relax its entry limits in planning areas that have zero dialysis centers. From 1997 to 2019, the NC dialysis CON program measured each planning area's need for dialysis stations as that number of dialysis stations operating at 3.2 patients-per-station necessary to treat a 6-month projection of the planning area's resident in-center dialysis patient population, net of its stock of existing stations. A planning area had a deficit if its stock of existing stations was less than its need. If a planning area with zero dialysis centers was reported in a SDR to have had a deficit of at least 9.5 stations (the "NC deficit threshold," hereafter), then a provider could apply to open a new dialysis center in that planning area. The NC dialysis CON program therefore became discontinuously more permissive of entry in planning areas with zero dialysis centers when those planning areas crossed the NC deficit threshold.

In this section, I leverage the 2007 WA policy change and the NC threshold-crossings to estimate

[20]Four point eight patients-per-station is 80% of 6 patients-per-station, i.e. full capacity for a station capable of treating three patients on each of a Monday-Wednesday-Friday and Tuesday-Thursday-Saturday cycle.

[21]For example, if a planning area was projected to have 48 patients and it had 6 stations, then it would need $\frac{48}{4.8} - 6 = 4$ additional stations operating at 4.8 patients-per-station to serve the projected patient population.

[22]Continuing with the above example, after the 2007 WA policy change, the planning area would need $\frac{48}{3.2} - 6 = 9$ additional stations.

[23]Figure A1 is a map of Washington highlighting the planning areas targeted by the 2007 WA policy change.

the effects of the WA and NC dialysis CON programs' entry limits in planning areas without pre-existing dialysis centers. In both Washington and North Carolina, these planning areas are all counties. Therefore, I refer to them as counties hereafter. I refer to the set of WA counties that had zero dialysis centers at the end of 2006 and were targeted by the 2007 WA policy change as the "target WA counties," hereafter.[24] I refer to the set of NC counties that crossed the NC deficit threshold between 1997 and 2019 while they had zero pre-existing dialysis centers as the "threshold-crossing NC counties," hereafter.[25] For brevity, I sometimes refer to the 2007 WA policy change and the threshold-crossings as the "events;" I refer to the target WA counties and the threshold-crossing NC counties as the "affected counties;" and I refer to the dates of the 2007 WA policy change and the threshold-crossings as the "event dates." I refer to the date eighteen months after each event as the event's "effective date"—that is, the date on which we might expect to see dialysis centers begin opening in response to the events.[26]

A. Did the 2007 WA policy change or the NC threshold-crossings spur entry?

In this section, I establish whether the events spurred providers to open dialysis centers in the affected counties. First, I leverage the within-county policy variation generated by the events using difference-in-differences, whereby I compare the affected counties to a sets of comparison counties before-and-after the events' effective dates. In this context, difference-in-differences identify the events' average treatment effects on the treated under parallel trends and no anticipation assumptions. In appendix A, I report supplemental evidence to strengthen the conceptual link between the events and the affected counties' subsequent entries.

I conduct the difference-in-differences analyses separately for Washington and North Carolina.

[24]The Washington State Department of Health (the "WA DOH," hereafter) identified Adams, Columbia, Douglas, Ferry, Garfield, Jefferson, Kittitas, Klickitat, Lincoln, Okanogan, Pacific, Pend Oreille, San Juan, Skamania, Stevens, and Wahakium counties as having zero dialysis centers at the end of 2006 (WSR 0624). However, Okanogan County already had a dialysis center according the USRDS data. Additionally, a provider filed an application to open a new dialysis center in Kittitas County before 2007. Although the application was reviewed after 2007, it was reviewed in accordance with the pre-2007 rules. Therefore, I exclude Okanogan and Kittitas counties from the list of target WA counties for the purposes of measuring the effect of the 2007 WA policy change on counties without pre-existing dialysis centers.

[25]The SDRs published between 1997 and 2019 report that Alexander, Davie, Gates, Greene, Haywood, Jones, Perquimans, Polk, Stokes, Swain, Warren, Washington, and Yadkin counties crossed the NC deficit threshold while having zero pre-existing dialysis centers. These are the threshold-crossing NC counties. In some analyses, Perquimans County is excluded from the group because its threshold-crossing occurred shortly before the end of my sample period.

[26]I assume that the events could not affect dialysis center openings instantaneously. The CON application process and dialysis center construction projects are time-consuming. I choose eighteen months because the first dialysis center opening that occurred in the affected counties after their events occurred eighteen months later. In North Carolina, only Polk County was observed to have had more than one threshold-crossing. I assign its event date to be its first observed threshold-crossing date.

I begin by constructing the WA and NC estimation samples. My WA estimation sample is a balanced county-month panel. The counties are the target WA counties and counties in nearby states that had zero dialysis centers in the month before the 2007 WA policy change's effective date (the "WA comparison counties," hereafter).[27] The months are January 2000 through December 2015. The NC estimation sample is a so-called "stacked" balanced county-month panel. I use the stacked data structure to address the negative weighting issue associated with conventional difference-in-differences estimators in settings where events occur in a staggered fashion (Cengiz et al., 2019; Gardner, 2021). I construct the NC estimation sample as follows. First, I collect the effective dates associated with each threshold-crossing. Second, for each effective date ($*$), I collect the threshold-crossing NC counties whose events' effective dates were ($*$) and the counties in nearby states that had zero dialysis centers in the month before ($*$) (the "NC comparison counties," hereafter).[28] Third, for each effective date, I construct a distinct balanced county-month panel of the foregoing counties spanning five calendar years before-and-after each panel's effective date.[29] Finally, I append these effective date-specific balanced county-month panels to create the stacked county-month panel.

Mathematically, I characterize the WA and NC estimation samples as follows. Let $\mathcal{C}$ index the set of effective dates associated with each county-month panel in the NC estimation sample. Let t^{WA} be the 2007 WA policy change's effective date and let t_c^{NC} be the effective date associated with $c \in \mathcal{C}$. Let $\mathcal{I}^{\text{WA}}$ be the set of counties that appear in the WA estimation sample and let $\mathcal{I}_c^{\text{NC}}$ be the set of counties that appear in panel c of the NC estimation sample. Let $\mathcal{I}_1^{\text{WA}} \subset \mathcal{I}^{\text{WA}}$ contain the target WA counties in the WA estimation sample and let $\mathcal{I}_{1c}^{\text{NC}} \subset \mathcal{I}_c^{\text{NC}}$ contain the threshold-crossing counties in panel c of the NC estimation sample. Likewise, let $\mathcal{I}_0^{\text{WA}}$ and $\mathcal{I}_{0c}^{\text{NC}}$ be their complements with respect to $\mathcal{I}^{\text{WA}}$ and $\mathcal{I}_c^{\text{NC}}$, respectively. Let $\mathcal{T}^{\text{WA}}$ be the set of months between January 2000 and December 2015 in the WA estimation sample, and let $\mathcal{T}_c^{\text{NC}}$ be the set of months within five calendar years of t_c. A unit of observation in the WA estimation sample is therefore indexed by $(i, t) \in \mathcal{I}^{\text{WA}} \times \mathcal{T}^{\text{WA}}$ and a unit of observation in the NC estimation sample is therefore indexed by $(c, i, t) \in \mathcal{C} \times \mathcal{I}_c^{\text{NC}} \times \mathcal{T}_c^{\text{NC}}$.

I use the WA and NC estimation samples to compare the affected counties' regression-adjusted trends in "having at least one dialysis center" before-and-after their effective dates to the comparison counties' contemporaneous trends. Let $\mathcal{L}^{\text{WA}}$ be a set of calendar half-years between 1H2000 and

[27] The nearby states are Oregon, Montana, Idaho, Wyoming, California, Nevada, Utah, Arizona, New Mexico, and Colorado.

[28] The nearby states are South Carolina, Georgia, Tennessee, and Virginia. I also include other North Carolina counties that did not yet have a dialysis center at the same time.

[29] At this step, I exclude Perquimans County from the set of threshold-crossing NC counties because its threshold-crossing occurred too close to the end of my sample period for me to construct a five calendar year window around its effective date.

2H2015, excluding 1H2008. Likewise, let $\mathcal{L}^{\text{NC}} := \{-10, ..., 10\} \setminus \{-1\}$ be a set of leads and lags measured in half-years. Let D_{it}^{WA} and D_{cit}^{NC} indicate in the WA and NC estimation samples respectively whether county i had a dialysis center in month t. Let $Z_{it} := \mathbb{1}\left[i \in \mathcal{I}_1^{\text{WA}}\right] \mathbb{1}\left[t \geq t^{\text{WA}}\right]$ and let $Z_{cit} := \mathbb{1}\left[i \in \mathcal{I}_{1c}^{\text{NC}}\right] \mathbb{1}\left[t \geq t_c^{\text{NC}}\right]$. Finally, let $L_{itl} := \mathbb{1}\left[i \in \mathcal{I}_1^{\text{WA}}\right] \mathbb{1}\left[t \in l\right]$ for some calendar half-year $l \in \mathcal{L}^{\text{WA}}$ and let $\mathcal{L}_{citl} := \mathbb{1}\left[i \in \mathcal{I}_{1c}^{\text{NC}}\right] \mathbb{1}\left[t \in t_c^{\text{NC}} + l\right]$ for some $l \in \mathcal{L}^{\text{NC}}$, where $t_c^{\text{NC}} + l$ is the calendar half-year l half-years after t_c^{NC}. I estimate the following linear regression equations with the WA estimation sample:

$$D_{it}^{\text{WA}} = \beta Z_{it}^{\text{WA}} + \Gamma X_{it} + \text{FE}_i + \text{FE}_t \times \text{PatPop}_{it} + \varepsilon_{it} \tag{2}$$

$$D_{it}^{\text{WA}} = \sum_{l \in \mathcal{L}^{\text{WA}}} \beta_l L_{itl}^{\text{WA}} + \Gamma X_{it} + \text{FE}_i + \text{FE}_t \times \text{PatPop}_{it} + \varepsilon_{it} \tag{3}$$

where X_{it} contains county characteristics and $\text{FE}_t \times \text{PatPop}_{it}$ is a month fixed effect interacted with county i's patient population in period t. Likewise, I estimate the following linear regression equations with the NC estimation sample:

$$D_{cit}^{\text{NC}} = \beta Z_{cit}^{\text{NC}} + \Gamma_c X_{cit} + \text{FE}_{ci} + \text{FE}_{ct} \times \text{PatPop}_{cit} + \varepsilon_{cit} \tag{4}$$

$$D_{cit}^{\text{NC}} = \sum_{l \in \mathcal{L}^{\text{NC}}} \beta_l L_{citl}^{\text{NC}} + \Gamma_c X_{cit} + \text{FE}_{ci} + \text{FE}_{ct} \times \text{PatPop}_{cit} + \varepsilon_{cit} \tag{5}$$

where X_{cit} is a vector of county characteristics and $\text{FE}_{ct} \times \text{PatPop}_{cit}$ is a cohort-specific month fixed effect interacted with the county's patient population.[30] Note that $(D_{cit}, X_{cit}, \text{PatPop}_{cit}) = (D_{c'it}, X_{c'it}, \text{PatPop}_{c'it})$ for all $(c, c') \in C^2$. In both analyses, I compute county-level cluster-robust standard errors to account for intra-county correlation in the errors, including correlation that arises due to repeating observations in the stacked dataset.

Table 13 reports my estimate of β and figure 1 plots my estimates of $(\beta_l : l \in \mathcal{L})$ from equations (2) and (3). Likewise, table 14 reports my estimate of β and figure 2 plots my estimates of $(\beta_l : l \in \mathcal{L})$ from equations (4) and (5). In both states, I find that the affected counties were differentially more likely to have a dialysis center after their effective dates than were their respective comparison counties contemporaneously. They were 23.4 percentage points more likely to have a dialysis center by 2015 (in WA) and 66 percentage points more likely to have a dialysis center after five years (in NC). On average, they were 20.4 percentage points more likely to have a dialysis center at some point between 2008 and 2015 (in WA) and 56.6 percentage points more likely to have

[30] Under the usual parallel trends and no anticipation assumptions, the stacked difference-in-differences method estimates a weighted average of the effective date-specific panels' average treatment effects on the treated (Gardner, 2021). Each panel's ATT's weight is proportional to the panel's sample size and the variance of its treatment indicator. That is, panels with (1) more treated and untreated units and (2) similar proportions of treated and untreated units have more weight.

a dialysis center at some point within five years (in NC). These estimates suggest that the events spurred entries in the affected counties, suggesting that the WA and NC dialysis CON programs' entry limits were binding in the affected counties before their events' effective dates.

B. Did the entrants on the WA and NC dialysis CON programs' policy margins affect patients?

In the foregoing section, I found that the affected counties were differentially more likely to have a dialysis center after their effective dates than were their respective comparison counties contemporaneously. In this section, I examine how the WA and NC dialysis CON programs' entry limits affected patients through their effect on dialysis center openings using instrumented difference-in-differences ("IV-DID," hereafter).

IV-DID identifies local average treatment effects on the treated, as follows. Consider a setting with two periods $t \in \{1, 2\}$. Assume that no units are exposed to the instrument in period 1, and let Z_i indicate whether some unit i is exposed to an instrument in period 2. Assume that no units are exposed to the treatment in period 1, and let each element of $\big(D_i(Z) : Z \in \{0, 1\}\big)$ indicate unit i's potential treatment status in period 2 given their exposure to the instrument. That is, let $D_i(1)$ indicate their treatment status in a world where they are exposed to the instrument, and let $D_i(0)$ indicate their treatment status in a world where they are not exposed to the instrument. The set of units $\mathcal{A} := \{i : D_i(1) = D_i(0) = 1\}$ are the always-takers, $\mathcal{N} := \{i : D_i(1) = D_i(0) = 0\}$ are the never-takers, and $\mathcal{C} := \{i : D_i(1) - D_i(0) = 1\}$ are the compliers. Assume that there are no defiers; i.e., that $\{i : D_i(1) - D_i(0) = -1\} = \emptyset$. Likewise, let $\Big(\big((Y_{i1}(D), Y_{i2}(D)\big) : D \in \{0, 1\}\Big)$ be unit i's potential outcomes in periods 1 and 2 given their potential exposure to the treatment in period 2. Assume that Z does not affect Y except through D. Let $(Z_i, D_i, Y_{i1}, Y_{i2})$ be unit i's realized instrument exposure, treatment status, and outcomes. The parameter of interest is $\mathbb{E}[Y_{i2}(1) - Y_{i2}(0) | i \in \mathcal{C}, Z_i = 1]$, which is the average difference between treated period 2 outcomes and untreated period 2 outcomes among units in the instrumented group that would have experienced a treatment if and only if they experienced the instrument. The Wald estimand is

$$\text{Wald} := \frac{\mathbb{E}[Y_{i2} - Y_{i1} | Z_i = 1] - \mathbb{E}[Y_{i2} - Y_{i1} | Z_i = 0]}{\mathbb{E}[D_i | Z_i = 1] - \mathbb{E}[D_i | Z_i = 0]}$$

which is a ratio of difference-in-differences. Under no anticipation and parallel trends assumptions, this is equivalent to $\mathbb{E}\Big[Y_{i2}\big(D_i(1)\big) - Y_{i2}\big(D_i(0)\big) | Z_i = 1\Big] / \mathbb{E}\big[D_i(1) - D_i(0) | Z_i = 1\big]$; i.e., it is the reduced-form average treatment effect on the treated of Z on Y ($*$) divided by the first-stage average treatment effect on the treated of Z on D ($**$). Since there are no defiers and since Z does not affect

Y except through D, the numerator is equal to $\mathbb{E}\left[Y_{i2}(1) - Y_{i2}(0)|i \in C, Z_i = 1\right]\mathbb{P}(i \in C|Z_i = 1)$. The denominator is equal to $\mathbb{P}(i \in C|Z_i = 1)$. Thus, we have that the Wald estimand is equal to $\mathbb{E}\left[Y_{i2}(1) - Y_{i2}(0)|i \in C, Z_i = 1\right]$. In other words, $(*)$ is the average effect of the instrument on the period 2 outcome among units exposed to the instrument. Since the instrument only affects outcomes through the treatment, and since the instrument only affects the treatment among the compliers, the ATT of Z on Y is the average effect of the treatment on compliers among the units exposed to the instrument scaled by the fraction of compliers among the units exposed to the instrument. The fraction of compliers among the units exposed to the instrument is $(**)$.

I conduct the IV-DID analyses separately for Washington and North Carolina. I begin by constructing new patient-level WA and NC estimation samples. I join the patient-month data I described in section I to the county-level WA and NC estimation samples I constructed in section III.A. The resultant WA estimation sample is a patient-month repeated cross-section nested within a balanced county-month panel. The resultant NC estimation sample is a stacked patient-month repeated cross-section nested within a stacked balanced county-month panel. Mathematically, I characterize the new WA and NC estimation samples as follows. Let p index patients and let $i(p,t)$ identify patient p's county in period t. Then a unit of observation in the WA estimation sample is indexed by $(p,t) \in \left\{(p,t) : (i(p,t),t) \in \mathcal{I}^{\text{WA}} \times \mathcal{T}^{\text{WA}}\right\}$. Likewise, a unit of observation in the NC estimation sample is indexed by $(c,p,t) \in \left\{(c,p,t) : (c,i(p,t),t) \in \mathcal{C} \times \mathcal{I}_c^{\text{NC}} \times \mathcal{T}_c^{\text{NC}}\right\}$.

I use the new WA and NC estimation samples to compare regression-adjusted mean outcome trends among patients in the affected counties before-and-after their events' effective dates to the contemporaneous trends among patients in the WA and NC comparison counties. I scale these difference-in-differences by the difference-in-differences in "having at least one in-county dialysis center." Let $\text{ZCTA}(p,t)$ identify patient p's ZCTA in period t. I estimate the following IV system with the WA estimation sample:

$$D^{\text{WA}}_{i(p,t)t} = \delta Z^{\text{WA}}_{i(p,t)t} + \Gamma X_{pt} + \text{FE}_{\text{ZCTA}(p,t)} + \text{FE}_t \times \text{PatPop}_{i(p,t)t} + \varepsilon_{pt} \tag{6}$$

$$Y_{pt} = \beta D^{\text{WA}}_{i(p,t)t} + \Gamma X_{pt} + \text{FE}_{\text{ZCTA}(p,t)} + \text{FE}_t \times \text{PatPop}_{i(p,t)t} + \varepsilon_{pt} \tag{7}$$

where X_{pt} is a vector of patient characteristics, including the patient's demographic information, health status at ESRD incidence, and county's characteristics. I also estimate the reduced-form event study:

$$Y_{pt} = \sum_{l \in \mathcal{L}^{\text{WA}}} \omega_l L^{\text{WA}}_{i(p,t)tl} + \Gamma X_{pt} + \text{FE}_{\text{ZCTA}(p,t)} + \text{FE}_t \times \text{PatPop}_{i(p,t)t} + \varepsilon_{pt} \tag{8}$$

Likewise, I estimate the following IV system with the NC estimation sample:

$$D^{\text{NC}}_{ci(p,t)t} = \delta Z^{\text{NC}}_{ci(p,t)t} + \Gamma_c X_{cpt} + \text{FE}_{c\text{ZCTA}(p,t)} + \text{FE}_{ct} \times \text{PatPop}_{ci(p,t)t} + \varepsilon_{cpt} \tag{9}$$

$$Y_{cpt} = \beta D^{\text{NC}}_{ci(p,t)t} + \Gamma_c X_{cpt} + \text{FE}_{c\text{ZCTA}(p,t)} + \text{FE}_{ct} \times \text{PatPop}_{ci(p,t)t} + \varepsilon_{cpt} \tag{10}$$

where X_{cpt} is a vector of patient characteristics, including the patient's demographic information, health status at ESRD incidence, and county's characteristics. I also estimate the reduced-form event study:

$$Y_{cpt} = \sum_{l \in \mathcal{L}^{\text{NC}}} \omega_l L^{\text{NC}}_{ci(p,t)tl} + \Gamma_c X_{cpt} + \text{FE}_{c\text{ZCTA}(p,t)} + \text{FE}_{ct} \times \text{PatPop}_{ci(p,t)t} + \varepsilon_{cpt} \tag{11}$$

In both analyses, I compute county-level cluster-robust standard errors to account for intra-county correlation in the errors, including correlation that arises due to repeating observations in the stacked dataset. I use ZCTA fixed effects instead of patient fixed effects because individuals with ESRD have low survival rates. Therefore, relatively few individual patients are observed for a significant period of time before-and-after an event's effective date. I discuss the implications of using ZCTA fixed effects in appendix B.

Tables 15-16 report my estimates of β from equation (7) for the WA estimation sample. Likewise, tables 17-18 report my estimates of β from equation (10) for the NC estimation sample. Under the foregoing IV-DID assumptions, the estimates of β may be interpreted as follows.

First, I find that patients living in the target WA counties or the threshold-crossing NC counties that got a dialysis center after their events' effective dates consequently had better access to dialysis. I find that they traveled approximately 21.0 fewer miles ([pre-event] baseline [in the target WA counties]: 33.0) and 8.08 fewer miles ([pre-event] baseline [in the threshold-crossing NC counties]: 18.8) on average in Washington and North Carolina, respectively. The baseline estimates (33.0 and 18.8 miles) are both significantly higher than the population average travel distance reported in table 1 (8.8 miles). The declines are significant in absolute terms: patients who traveled to and from their dialysis center thrice weekly for HD traveled 6,552 fewer miles per year and 2,527 fewer miles per year on average in Washington and North Carolina, respectively. I also find that patients living in the affected counties that got a dialysis center after their events' effective dates consequently used HHD 7.5 percentage points less often (baseline: 3.3%) and 1.3 percentage points less often (baseline: 0.5%) on average in Washington and North Carolina, respectively. This suggests that a lack of access to a dialysis center can manifest itself not only in patients traveling farther for in-center treatment provided by dialysis centers' medical staff, but also in patients foregoing travel all

together by taking responsibility for their own care at home.[31] Figures 3 and 4 plot the corresponding estimates of $(\omega_l : l \in \mathcal{L})$ from equation (8) and (11).

Second, I find that patients living in the target WA counties or the threshold-crossing NC counties that got a dialysis center after their events' effective dates consequently had access to more resources at their chosen dialysis centers. I find that they were treated at dialysis centers with 0.075 more stations-per-patient (baseline: 0.237) and 0.085 more stations-per-patient (baseline: 0.256) on average in Washington and North Carolina, respectively. I find that they were treated at dialysis centers with 0.024 more FTE nurses-per-patient (baseline: 0.052 nurses-per-patient) on average in North Carolina. Finally, I find that they were treated at dialysis centers with 0.016 more FTE dieticians-per-patient (baseline 0.009) and 0.007 more dieticians-per-patient (baseline: 0.010) on average in Washington and North Carolina, respectively. Figures 5 and 6 plot the corresponding estimates of $(\omega_l : l \in \mathcal{L})$ from equations (8) and (11).

Finally, I find that patients living in the target WA counties that got a dialysis center after their events' effective dates consequently experienced fewer hospitalizations. I find that they were 6.9 percentage points less likely to be hospitalized in any given month for any reason (baseline: 12.3%) on average. Most of this decline is attributable to a 6.0 percentage point decline in the likelihood of a cardiovascular event (baseline: 11.4%) on average. I do not find evidence that they were differentially less likely to have fewer than 12 HD-equivalent dialysis sessions per month, that their URR was significantly affected, or that their mortality rates were significantly affected. Likewise, I do not find evidence that patients living in the threshold-crossing NC counties that got a dialysis center after their events' effective dates consequently experienced better health outcomes. Figures 7-10 plot the corresponding estimates of $(\omega_l : l \in \mathcal{L})$ from equations (8) and (11).

C. By how much did the entrants on the WA and NC dialysis CON programs' policy margins improve patient welfare?

Taken together, the findings in sections III.A and III.B indicate that dialysis CON programs are important determinants of market structure, treatment access, and, in some contexts, patient health. In this section, I measure the marginal centers' overall contributions to patient welfare using a structural model of patient preferences.

I model patient utility as follows. Let u_{pjt} be patient p's utility for being treated at dialysis center j in period t, such that $u_{pjt} = -\gamma \text{TravelDistance}_{pjt} + \delta_j + \varepsilon_{pjt}$ where δ_j is a facility fixed

[31] This is consistent with recent work by Pattharanitima et al. (2021), who documented that patients who live farther from their nearest dialysis center tend to use at-home dialysis more often.

effect absorbing all fixed dialysis center characteristics and ε_{pjt} is an i.i.d. extreme value taste shock. Let patient p choose in each period t to be treated at any dialysis center within 100 miles, from one of several chain-specific outside options located 100 miles away, or from one of several chain-specific at-home dialysis programs for which TravelDistance is equal to zero. Let each patient in each period choose a center j^*_{pt} from their choice set $\mathcal{J}_{pt}$ such that $j^*_{pt} := \arg\max_{j \in \mathcal{J}_{pt}} u_{pjt}$.

I estimate γ and the alternative-specific fixed effects δ_j separately for patients included in the WA and NC analyses. My WA estimation sample is a sample of patient-years consisting of all patients living in the target WA counties and the WA comparison counties in each year between 2000 and 2015. My NC estimation sample is a sample of patient-years consisting of all patients living in the threshold-crossing NC counties and the NC comparison counties in each year between 1993 and 2015.[32] I use my estimates to construct a patient-level welfare measure $\hat{u}_{pt} := \ln\left(\sum_{j \in \mathcal{J}_p} \exp\left(-\text{TravelDistance}_{pjt} + \frac{1}{\hat{\gamma}}\hat{\delta}_j\right)\right)$. Note that since I do not observe patients making dollar-valued transactions, I cannot measure patient welfare in dollars. I therefore express patient welfare in MTEs—that is, I interpret a one unit increase in $\hat{u}_{pjt}$ to be equivalent to the gain a patient feels when they travel to a dialysis center one mile closer to their homes for in-center dialysis.

I use this patient welfare measure as an outcome in equations (6)-(11). Tables 19 and 20 present the results. Figure 11 plots the corresponding estimates of $(\omega_l : l \in \mathcal{L})$ from equations (8) and (11). I find that patients' revealed preferences imply that patients living in the affected counties that got a dialysis center after their events' effective dates consequently experienced a welfare gain equal to 14.3 MTEs (in WA) and 11.5 MTEs (in NC) per one-way trip.[33] Panel (A) of tables 21 and 22 aggregates these estimates to the county-month level in Washington and North Carolina, respectively. I find that patients' revealed preferences imply that dialysis centers on the WA and NC dialysis CON programs' policy margins contributed 10,500 MTEs to their counties' patient populations each month, on average.

D. How did the entrants on the WA and NC dialysis CON programs' policy margins affect total welfare?

The foregoing calculations estimated the marginal centers' contributions to patient welfare, as measured by the patients' revealed preferences. In this section, I take two additional steps to

[32]The effective date of the first threshold-crossing that I observe is in 1998. Therefore, 1993 is the earliest calendar year in the five calendar year event windows. The effective date of the last threshold-crossing for which I can construct a five calendar year event window is in 2011. Therefore, 2015 is the last calendar year in the analysis.

[33]These estimates differ from the estimates of the marginal centers' effects on patients' travel distances to their chosen dialysis centers. These differences are attributable to changes in the mix of the dialysis center fixed effects as well as to ordinary changes in the geographic distribution of patients relative to *all* dialysis centers in their choice sets.

measure the marginal centers' contributions to total welfare. Tables 21-22 summarize the results.

In the first step, I estimate the marginal centers' contributions to fixed costs. Although the event windows span 1993-2015, the annual fixed cost data published by Medicare in HCRIS span 2011-2016. I therefore impute dialysis centers' annual fixed costs before 2011 using their observable characteristics. I use my 2011-2016 facility-year sample to estimate

$$\ln\big(\text{FixedCost}_{it}\big) = \beta X_{it} + \varepsilon_{it} \tag{12}$$

where X_{it} is a vector of dialysis center characteristics, including their age, state, chain affiliation, crowdedness, and stock of dialysis stations. Table A1 reports the results. I use one-twelfth of the predicted value $\exp\big(\ln(\widehat{\text{FixedCost}}_{it})\big)$ as my measure of dialysis centers' monthly fixed costs. I aggregate dialysis centers' monthly fixed costs to the county-month level and merge them into the county-level estimation samples I described in section III.A. I estimate IV-DID systems as in equations (6)-(7) and (9)-(10), which (1) relate whether a county has a dialysis center to whether the county experienced an event and (2) relate the county's total fixed costs to whether the county has a dialysis center. Tables A2-A3 and figure A2 report the results. I find evidence that affected counties that experienced an entry because the WA and NC dialysis CON programs' relaxed their entry limits consequently had \$48,000 and \$35,000 higher fixed costs per month, respectively. These estimates are reported in tables 21 and 22 in panel (B).

In the second step, I consider two missing ingredients. The first missing ingredient is the dollar value of an MTE. Let this be denoted by κ_1. The second missing ingredient is the marginal centers' contribution to total welfare through their effect on hospitalization rates. Due to imperfect information and moral hazard, dialysis patients may not fully internalize the consequences of their treatment choices on their health outcomes or their health resource utilization. Consequently, revealed preferences estimates of patient welfare may understate the marginal centers' welfare contributions in Washington because they exclude part of the marginal centers' effects on patients' hospitalization rates. Let κ_2 be the cost of a single hospitalization *not* accounted for in patients' revealed preferences.

I combine these missing ingredients with the foregoing patient welfare and fixed cost estimates as follows. In section III.B, I found that patients in the target WA counties that got their first dialysis center because of the 2007 WA policy change consequently experienced 6.9 percentage points fewer hospitalizations per month. In table 21 panel (C), I show that this corresponds to approximately 2.1 fewer hospitalizations per county-month. Therefore, the marginal centers raised total welfare

in the target WA counties if (κ_1, κ_2) are such that

$$\$48,000 \leq 10,500\text{MTE} \times \kappa_1 + 2.1 \times \kappa_2 \tag{13}$$

Table 21 panel (D) plots the values of (κ_1, κ_2) that zero out equation (13). In North Carolina, I did not find evidence that the marginal centers reduced patients' hospitalization rates. Therefore, they raised total welfare in the threshold-crossing NC counties if

$$\$35,000 \leq 10,500\text{MTE} \times \kappa_1 \tag{14}$$

Table 21 panel (D) characterizes the minimum value of κ_1 that satisfies equation (14).

I benchmark these findings with proxies for (κ_1, κ_2). The American Automobile Association estimated in 2010 that the average vehicle operating cost was approximately \$1.05 per mile (AAA, 2010).[34] If the time value of an hour is between \$2.00-\$15.00, then the time value of traveling a mile is about \$0.05-\$0.38.[35][36] If each dialysis patient is chauffeured by a relative or friend and if each chauffeur makes twice as many trips as each patient, then the foregoing estimates suggest that $\kappa_1 \in$ [\$1.20, \$2.19].[37] Together with equation (14), this suggests that the dialysis centers on the NC dialysis CON program's policy margin were unlikely to increase welfare in the short run. If $\kappa_1 = \$1.70$—the median of $[\$1.20, \$2.19]$—then in Washington, the marginal centers would have increased welfare in the short run if $\kappa_2 \geq \$14,357$. By comparison, the average cost of a hospitalization for Medicare patients was approximately \$12,000 in 2008 (Moore et al., 2014). Taken together, these back-of-the-envelope calculations imply that if the WA and NC dialysis CON programs had not relaxed their entry limits in the affected counties, then total welfare would have grown (at patients' expense).

[34]This is equal to the \$0.74 per driving mile reported in AAA (2010) times 1.417 driving miles per straight-line mile (Boscoe, 2012). All miles reported in this paper are straight-line miles, unless otherwise noted.

[35]I rescale \$2.00 and \$15.00 by 60 minutes to arrive at \$0.03 and \$0.25 per minute. I rescale these by 1.5 minutes per straight-line mile to arrive at \$0.05 and \$0.38 per straight-line mile (Boscoe, 2012).

[36]For reference, Small et al. (1999) found that in a 1995 survey of drivers, the time value of traveling was \$2.64 per hour for individuals who earned \$15,000 per year and \$8.05 per hour for individuals who earned \$95,000 per year. For further reference, a typical rule of thumb in the transportation literature is that the value of travel time is 50% of wages (Parry et al., 2007).

[37]Eliason (2021) estimated that the dollar value of an MTE for dialysis patients was approximately \$1.86 with similar back-of-the-envelope calculations.

IV. Evidence From the NC Dialysis CON Program's Entry Limits in Counties With Incumbents

In section III, I leveraged policy variation generated by the WA and NC dialysis CON programs' entry limits in counties without any dialysis centers—that is, counties with relatively low patient populations. However, dialysis CON programs may also influence market structure and welfare in a much larger region. In this section, I analyze 22 years of CON applications and the data underlying the NC dialysis CON program's determinations of where and when new centers were "needed." I combine these data with policy variation generated by the NC dialysis CON program's entry limits in counties with incumbents to examine the entry limits' competitive effects.[38]

Between 1997 and 2019, the NC dialysis CON program's entry policy in counties with incumbents was as follows. If a county with incumbents had a deficit of at least 9.5 stations (i.e., if the NC deficit threshold was triggered) and if no existing dialysis center was serving fewer than 3.2 patients-per-station (the "NC utilization threshold," hereafter), then a provider could apply to open a new dialysis center in that county. Providers had opportunities to apply to open new dialysis centers during semiannual application cycles that began when the NC dialysis CON program published a SDR reporting each facility's utilization rate and each county's station deficit.

I constructed a county-half-year sample of data published by the NC SDRs between 1997 and 2019. I link these data to indicators of whether providers filed applications to open new dialysis centers. Figure 12 plots the joint distribution of dialysis station deficits and countywide minimum utilization rates in this sample. It separates the region where both the NC deficit threshold and the NC utilization threshold were triggered from the region where either or both thresholds were not triggered. It also marks with an $\times$ those county-half-years where a provider filed an application to open a new dialysis center and the NC dialysis CON program approved the project. In panel (a), the figure marks applications that described that they would only use new dialysis stations. In panel (b), the figure marks applications that described that they would transfer previously approved stations from an existing center in the county or an adjacent county.[39]

I make three observations. First, figure 12 suggests that the NC dialysis CON program was permissive of applications to open a new dialysis center in a given county even when either or both thresholds were not triggered if those applications were filed by incumbents and transferred

[38]Six NC counties were combined into two planning areas consisting of three counties each during my sample period. I exclude these planning areas. The remaining NC planning areas are counties. I therefore refer to them as counties hereafter.

[39]Only chains that have a facility operating in a given county can use stations from an adjacent county to open a new facility.

stations from an existing center in that county or an adjacent county. Second, it suggests that the NC dialysis CON program was not similarly permissive of applications filed by outsiders: all but one approved application to open a totally new dialysis center were filed only when both thresholds were triggered. This suggests that if either the NC deficit threshold or the NC utilization threshold were not triggered, then outsiders could not easily open new dialysis centers in a given county; but incumbents could. Moreover, incumbents have some control over when the NC deficit threshold is triggered. For instance, if an incumbent expands their centers' capacities at pace with their county's resident in-center dialysis patient population, then the NC dialysis CON program may never find that the county needs at least 9.5 additional dialysis stations. Finally, I observe that there were very few county-half-years where the NC deficit threshold was triggered in counties with incumbents. That is, there are very few data points in the top half of figure 12.

Taken together, these observations suggest that the NC dialysis CON program conferred market power upon incumbents by insulating them from potential competition. Perhaps unsurprisingly, I find that in South Carolina, Georgia, Tennessee, and Virginia, approximately sixteen percent of new dialysis centers that opened in counties with an incumbent were owned by an outsider. In North Carolina, I observe that this occurred about half as often. Furthermore, table 23 reports regression-adjusted differences between NC dialysis centers and SC, GA, TN, and VA dialysis centers. It shows that NC dialysis centers tended to have fewer competitors within 10 miles and their nearest competitors were farther away, on average. However, it remains unclear whether incumbents meaningfully exercised this market power. Existing research suggests that local market power is a significant determinant of treatment quality (Eliason, 2021) and that centers' medical personnel are important inputs to the production of treatment quality (Grieco and McDevitt, 2017). Consistent with these findings, table 23 also shows that NC dialysis centers tended to have fewer more-credentialed staff members per patient (nurses and dieticians), and more less-credentialed staff members per patient (PCTs).

V. Conclusion

Can entry barriers in health care provider markets raise welfare? In this study, I estimated the effects of dialysis CON programs' entry limits by leveraging within-county variation in their stringency. I found that the WA and NC dialysis CON programs' entry limits were binding in counties without any dialysis centers. I found that marginal centers significantly improved patient access, lowered hospitalization rates, and contributed to patient welfare the utility value of traveling 275-344 fewer miles per month; but my back-of-the-envelope calculations suggested that they contributed even

more to fixed costs. Taken together, these findings suggest that regulatory entry barriers in some geographic provider markets can raise welfare (at patients' expense).

But they may be more harmful elsewhere. In North Carolina, I found evidence that the NC dialysis CON program conferred market power upon incumbents by insulating them from potential competition. If incumbents exercise this market power by raising prices or lowering quality, then CON programs may cause patients to travel farther, wait longer, or pay more for poorer health care. At the same time, my findings in North Carolina also raise questions about whether CON programs' competitive effects indirectly help them overcome their "[in]ability to [...] act affirmatively" (Blumstein and Sloan, 1978) to improve treatment access. If providers anticipate that CON programs will insulate them from potential competition when they are the first to enter a geographic market, then they may enter that geographic market *earlier* than they would have otherwise. Whether providers exercise the market power conferred upon them by CON programs; and whether CON programs improve treatment access through this indirect mechanism remains unknown. I leave these questions for future research.

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	Mean	SD	10%ile	Median	90%ile
Chosen Facility Characteristics					
Patient Volume	103.73	64.06	37.00	91.00	185.00
Stations	21.11	10.14	10.00	20.00	33.00
Stas. Per Pat.	0.24	0.13	0.13	0.21	0.37
Nurses	7.12	5.19	2.50	6.00	13.00
Nurs. Per Pat.	0.08	0.06	0.04	0.06	0.12
PCTs	8.69	6.02	2.00	8.00	16.00
PCTs. Per Pat	0.09	0.05	0.04	0.09	0.12
Dieticians	1.02	0.60	0.50	1.00	2.00
Diets. Per Pat	0.01	0.01	0.01	0.01	0.02
Hospitalizations					
1[Any]	0.14	0.35	0.00	0.00	1.00
1[Infection]	0.06	0.24	0.00	0.00	0.00
1[Cardio. Event]	0.13	0.34	0.00	0.00	1.00
1[Acc. Rel. Event]	0.03	0.17	0.00	0.00	0.00
Travel and At-home Dialysis Utilization					
Mi. to Center	8.78	12.14	0.00	5.11	20.86
1[HHD]	0.01	0.12	0.00	0.00	0.00
1[PD]	0.10	0.30	0.00	0.00	1.00
Dialysis Adequacy and Treatment Adherence					
1[URR <60%]	0.04	0.21	0.00	0.00	0.00
1[URR 60-65%]	0.05	0.21	0.00	0.00	0.00
1[URR 65-70%]	0.15	0.36	0.00	0.00	1.00
1[URR 70-75%]	0.29	0.46	0.00	0.00	1.00
1[URR >75%]	0.43	0.49	0.00	0.00	1.00
#[HD Equiv. Sess.]	11.70	5.58	2.00	13.00	14.00
1[< 12 HD Equiv. Sess.]	0.18	0.38	0.00	0.00	1.00
Demographics and Other Characteristics at ESRD Incidence					
Age	61.81	16.06	39.00	64.00	81.00
1[White]	0.54	0.50	0.00	1.00	1.00
1[Black]	0.28	0.45	0.00	0.00	1.00
1[Hispanic]	0.11	0.31	0.00	0.00	1.00
1[Asian]	0.03	0.17	0.00	0.00	0.00
1[Female]	0.45	0.50	0.00	0.00	1.00
Height (cm)	167.95	11.75	153.00	168.00	182.88
Weight (kg)	80.06	23.95	54.00	76.00	110.00
1[Diabetes]	0.49	0.50	0.00	0.00	1.00
1[Hypertension]	0.33	0.47	0.00	0.00	1.00
1[Glom.]	0.13	0.33	0.00	0.00	1.00
1[Cyst.]	0.03	0.17	0.00	0.00	0.00
1[Employed FT]	0.17	0.37	0.00	0.00	1.00
1[% Employed]	0.28	0.45	0.00	0.00	1.00
Transplant Outcome					
1[Ever Gets Tx.]	0.13	0.34	0.00	0.00	1.00
Insurance Status					
1[Medicare Primary]	0.80	0.40	0.00	1.00	1.00

Tab. 1. This table reports descriptive statistics about dialysis patients. They are made using a 20% random sample of patient-months. The sample includes 22 million patient-months encompassing 570,000 patients. See the discussion near page 10. Data source(s): USRDS.

	Mean	SD	10%ile	Median	90%ile
Capacity and Utilization					
Stations	17.36	8.32	8.00	16.00	27.00
Stas. Per Pat.	0.31	0.22	0.15	0.26	0.51
Nurses	5.01	3.57	2.00	4.00	9.00
Nurs. Per Pat.	0.08	0.05	0.04	0.07	0.12
PCTs	6.29	4.77	1.50	5.00	12.00
PCTs. Per Pat	0.09	0.07	0.04	0.09	0.13
Dieticians	0.82	0.47	0.50	1.00	1.00
Diets. Per Pat	0.01	0.01	0.01	0.01	0.03
Chain Affiliation					
1[DaVita]	0.28	0.45	0.00	0.00	1.00
1[Fresenius]	0.35	0.48	0.00	0.00	1.00
1[Independent]	0.10	0.29	0.00	0.00	0.00
1[Other Chain]	0.27	0.45	0.00	0.00	1.00
Patient Volume					
All Patients	69.67	49.16	19.00	60.00	133.00
HD Patients	62.40	43.01	15.00	55.00	118.00
HHD Patients	0.90	5.16	0.00	0.00	1.00
PD Patients	6.57	13.73	0.00	0.00	22.00
All Home Pats.	7.47	15.56	0.00	0.00	24.00
At-home Dialysis Availability					
1[Has HHD Patient]	0.16	0.36	0.00	0.00	1.00
1[Has PD Patient]	0.44	0.50	0.00	0.00	1.00
1[Has Any Home Patient]	0.46	0.50	0.00	0.00	1.00

Tab. 2. This table reports descriptive statistics about dialysis centers. The sample includes 1.3 million center-years encompassing 7,300 centers. See the discussion near page 10. Data source(s): USRDS.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1[Facility]	Facilities	Facilities	Stations	Stations	Stations Per Resid. Patient	Stations Per Resid. Patient
1[CON]	0.126**	-0.251**	-0.478***	-2.747*	-5.105***	-0.009	-0.070***
	(0.058)	(0.099)	(0.157)	(1.407)	(1.835)	(0.021)	(0.014)
Year FE	Y	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y	Y
$1[\text{Facs.} > 0]$	-	-	Y	-	Y	-	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	0.547	1.983	3.500	33.003	58.208	0.227	0.361
N	36,619	36,619	20,879	36,518	20,778	31,849	20,711
Clusters	50	50	50	50	50	50	50
Adj. R^2	0.355	0.960	0.960	0.976	0.976	0.090	0.116

State-level cluster-robust SEs in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 3. This table reports my estimates of β in equation (1). They are computed from a sample of county-years spanning 2005-2016. Models (3), (5), and (7) subset the data to only those county-years with at least one dialysis center. The table shows that counties in dialysis CON states are more likely to have a dialysis center, but have fewer centers, fewer stations, and fewer stations-per-resident-patient. See the discussion near page 15. Data source(s): USRDS.

	(1) Nurses	(2) Nurses Per Resid. Patient	(3) Diets.	(4) Diets. Per Resid. Patient	(5) Techs.	(6) Techs. Per Resid. Patient
1[CON]	0.056	-0.002	-0.111*	-0.000	-0.253	0.008
	(1.012)	(0.007)	(0.066)	(0.001)	(0.671)	(0.006)
Year FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
1[Facs. > 0]	-	-	-	-	-	-
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	9.898	0.068	1.544	0.011	11.170	0.057
N	36,513	31,844	36,513	31,844	36,513	31,844
Clusters	50	50	50	50	50	50
Adj. R^2	0.950	0.096	0.970	0.022	0.985	0.107

	(7) Nurses	(8) Nurses Per Resid. Patient	(9) Diets.	(10) Diets. Per Resid. Patient	(11) Techs.	(12) Techs. Per Resid. Patient
1[CON]	0.013	-0.019*	-0.195*	-0.003*	-0.355	-0.001
	(1.671)	(0.010)	(0.112)	(0.002)	(0.991)	(0.006)
Year FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
1[Facs. > 0]	Y	Y	Y	Y	Y	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	17.413	0.108	2.720	0.018	19.628	0.090
N	20,773	20,706	20,773	20,706	20,773	20,706
Clusters	50	50	50	50	50	50
Adj. R^2	0.948	0.068	0.970	0.030	0.985	0.006

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 4. This table reports my estimates of β in equation (1). They are computed from a sample of county-years spanning 2005-2016. Models (7)-(12) subset the data to only those county-years with at least one dialysis center. Models (1)-(6) show that counties in dialysis CON states do not have statistically significantly different numbers of staff-per-patient. Models (7)-(12) show that counties in dialysis CON states with at least one dialysis center have slightly fewer nurses- and dieticians-per-resident patient, though these differences are not statistically significant at the 95% level. See the discussion near page 15. Data source(s): USRDS.

	(1) All Patients	(2) HD Patients	(3) HHD Patients	(4) PD Patients	(5) All Home Patients
1[CON]	13.921***	11.689***	0.552***	1.766***	2.318***
	(4.145)	(3.900)	(0.154)	(0.482)	(0.540)
Year FE	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	65.114	59.523	0.892	5.809	6.701
N	70,948	69,782	69,782	69,782	69,782
Clusters	50	50	50	50	50
Adj. R^2	0.134	0.144	0.016	0.035	0.035

	(6) Stations Per Pat.	(7) Nurses Per Pat.	(8) Dietic. Per Pat.	(9) PCTs Per Pat.	(10) Offers At-Home
1[CON]	-0.058***	-0.002	-0.002*	-0.001	0.049*
	(0.008)	(0.013)	(0.001)	(0.005)	(0.026)
Year FE	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	0.326	0.092	0.016	0.086	0.420
N	66,650	66,631	66,631	66,631	69,782
Clusters	50	50	50	50	50
Adj. R^2	0.044	0.018	0.030	0.004	0.034

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 5. This table reports my estimates of β in equation (1). They are computed from a sample of center-years spanning 2005 to 2016. Models (1)-(6) show that centers in dialysis CON states have higher patient volumes than centers in other states. Models (6)-(9) show that they have fewer stations-per-patient and fewer staff-per-patient, though the staff-per-patient estimates are not statistically significantly different from zero at the 95% level. Model (10) show that centers in dialysis CON states are more likely to have at least one at-home dialysis patient, though this estimate is not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1) 1st Nearest Competitor	(2) 3rd Nearest Competitor	(3) 5th Nearest Competitor	(4) 1st Nearest Same-Chain	(5) 3rd Nearest Same-Chain	(6) 5th Nearest Same-Chain
1[CON]	1.254	1.986	2.887**	1.462	2.336	2.898
	(1.079)	(1.298)	(1.300)	(2.984)	(2.688)	(2.486)
Year FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	9.092	16.617	20.405	18.966	25.958	30.438
N	70,948	70,948	70,948	70,948	70,948	70,948
Clusters	50	50	50	50	50	50
Adj. R^2	0.334	0.526	0.567	0.098	0.172	0.215

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 6. This table reports my estimates of β in equation (1). They are computed from a sample of center-years spanning 2005 to 2016. Columns (1)-(3) show that centers in dialysis CON states are slightly farther away from their first, third, and fifth nearest competitors (that is, centers belonging to different chains or other independent centers), and columns (4)-(6) similarly show that they are slightly farther away from their first, third, and fifth nearest sister-centers (that is, centers belonging to the same chain). However, most estimates are not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1) Distance	(2) Stations Per Pat.	(3) 1[Offers At-Home]	(4) Nurses Per Pat.	(5) Dietic. Per Pat.	(6) PCT Per Pat.
1[CON]	-0.665	-0.028**	0.056**	-0.000	-0.001**	-0.001
	(0.482)	(0.011)	(0.024)	(0.009)	(0.000)	(0.006)
Month FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
Subsample	.05	.05	.05	.05	.05	.05
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	8.104	0.254	0.512	0.076	0.012	0.086
N	2,748,182	2,806,830	2,824,573	2,805,407	2,805,407	2,805,407
Clusters	50	50	50	50	50	50
Adj. R^2	0.133	0.081	0.039	0.072	0.055	0.019

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 7. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states visit dialysis centers that have fewer stations-per-patient and fewer dieticians-per-patient, but are more likely to have at least one at-home dialysis patient. It also shows that they choose dialysis centers slightly closer to their homes, but this estimate is not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1) Nearest Center	(2) 10%ile S/P	(3) 25%ile S/P	(4) 50%ile S/P	(5) 75%ile S/P	(6) 90%ile S/P
1[CON]	-0.256	-0.021	0.427	1.720	4.650***	6.924***
	(0.348)	(0.471)	(0.670)	(1.188)	(1.299)	(1.522)
Month FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
Subsample	.05	.05	.05	.05	.05	.05
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	3.691	4.039	4.975	7.287	11.375	18.235
N	2,914,540	2,918,910	2,918,910	2,918,910	2,918,910	2,918,910
Clusters	50	50	50	50	50	50
Adj. R^2	0.274	0.251	0.219	0.229	0.287	0.335

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 8. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states live 4.6-6.9 miles farther from dialysis centers with relatively high stations-per-patient. It also shows that their nearest dialysis center is slightly closer to their homes, though this estimate is not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1) 1[HD]	(2) 1[HHD]	(3) 1[PD]	(4) 1[Any Home]
1[CON]	-0.006	0.007	-0.001	0.006
	(0.009)	(0.004)	(0.006)	(0.009)
Month FE	Y	Y	Y	Y
County Char.	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y
Subsample	.05	.05	.05	.05
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	0.900	0.014	0.086	0.100
N	2,920,422	2,920,422	2,920,422	2,920,422
Clusters	50	50	50	50
Adj. R^2	0.069	0.019	0.067	0.069

State-level cluster-robust SEs in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 9. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states are slightly more likely to use at-home dialysis, but these estimates are not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1)	(2)	(3)
	1[Infection]	1[Cardio. Event]	Any
1[CON]	-0.004**	-0.006**	-0.006*
	(0.002)	(0.003)	(0.003)
Month FE	Y	Y	Y
County Char.	Y	Y	Y
Pat. Char.	Y	Y	Y
Subsample	.05	.05	.05
Est. Years	2005-2015	2005-2015	2005-2015
$\hat{Y}\|X = 0$	0.065	0.132	0.135
N	1,634,480	1,634,480	1,634,480
Clusters	50	50	50
Adj. R^2	0.008	0.014	0.014

State-level cluster-robust SEs in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 10. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states are slightly less likely to experience a hospitalization, a hospitalization associated with an infection, and a hospitalization associated with a cardiovascular event. See the discussion near page 16. Data source(s): USRDS.

	(1) Sessions	(2) 1[Fewer Than 12 Sessions]
1[CON]	0.120*	-0.015**
	(0.071)	(0.006)
Month FE	Y	Y
County Char.	Y	Y
Pat. Char.	Y	Y
Subsample	.05	.05
Est. Years	2005-2016	2005-2016
$\hat{Y}\|X = 0$	11.894	0.184
N	1,994,398	1,760,956
Clusters	50	50
Adj. R^2	0.036	0.024

State-level cluster-robust SEs in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 11. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states are slightly less likely to receive fewer than 12 HD-equivalent treatments per month. See the discussion near page 16. Data source(s): USRDS.

	(1) URR $< 60\%$	(2) URR $60-65\%$	(3) URR $65-70\%$	(4) URR $70-75\%$	(5) URR $> 75\%$	(6) URR $< 65\%$
1[CON]	0.002	-0.003	-0.009	-0.009	0.020	-0.001
	(0.003)	(0.002)	(0.007)	(0.006)	(0.014)	(0.004)
Month FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
Subsample	.05	.05	.05	.05	.05	.05
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	0.036	0.035	0.132	0.288	0.444	0.071
N	1,821,190	1,821,190	1,821,190	1,821,190	1,821,190	1,821,190
Clusters	50	50	50	50	50	50
Adj. R^2	0.016	0.018	0.029	0.021	0.091	0.032

State-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 12. This table reports my estimates of β in equation (1). They are computed from a 5% random sample of patient-months spanning 2005 to 2016. It shows that patients in dialysis CON states are slightly more likely to have a URR at or above 75% and slightly less likely to have a URR below 65%, however these estimates are not statistically significantly different from zero at the 95% level. See the discussion near page 16. Data source(s): USRDS.

	(1)
	1[Has A Center]
Target WA	0.204**
county × Post	(0.090)
Month FE	Y
County FE	Y
Pat. Pop. Chars.	Y
Window	$[2000, 2015]$
T. Units	14
C. Units	207
Baseline Y	0.00
N	42,431
Clusters	221
Adj. R^2	0.48

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 13. This table reports my estimates of β in equation (2). It shows that the likelihood of having at least one dialysis center grew more in the target WA counties after the 2007 WA policy change's effective date than it grew in the WA comparison counties contemporaneously. See the discussion near page 21. Data source(s): USRDS.

	(1)
	1[Has A Center]
Threshold-crossing	0.566***
NC county × Post	(0.096)
Month FE	Y
County FE	Y
Pat. Pop. Chars.	Y
Yr. Range	[1993, 2015]
Window	[-10, 9]
T. Units	12
C. Units	225
Baseline Y	0.00
N	202,645
Clusters	226
Adj. R^2	0.46

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 14. This table reports estimates of β from equation (4). It shows that the likelihood of having at least one dialysis center grew more in the threshold-crossing NC counties after their threshold-crossings' effective dates than it grew in the NC comparison counties contemporaneously. See the discussion near page 21. Data source(s): USRDS.

	(1) Miles to Chosen Center	(2) 1[Treated In Own County]	(3) Stations Per Patient At Chosen Center	(4) Nurses Per Patient At Chosen Center	(5) Diets. Per Patient At Chosen Center	(6) PCTs Per Patient At Chosen Center
1[Center In County]	-20.9921***	0.4816***	0.0746*	0.0320**	0.0163***	0.0120
	(3.5975)	(0.0545)	(0.0427)	(0.0145)	(0.0048)	(0.0170)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	[2000, 2015]	[2000, 2015]	[2000, 2015]	[2004, 2015]	[2004, 2015]	[2004, 2015]
Window (Yrs.)	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-4, 6]$	$[-4, 6]$	$[-4, 6]$
T. ZCTAs	93	94	94	92	92	92
C. ZCTAs	835	914	913	871	871	871
B-line Y	32.951	0.000	0.237	0.075	0.009	0.119
F-Stat.	18.3	17.8	17.9	16.3	16.3	16.3
N	266,244	298,682	296,896	240,578	240,578	240,578
Clusters	215	219	219	218	218	218
Adj. R^2	0.111	0.360	0.059	0.008	0.037	0.006

County-level cluster-robust SEs in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 15. This table reports estimates of β from equation (7). Under the IV-DID assumptions discussed in the main text, it shows that patients in the target WA counties that experienced their first dialysis center opening after the 2007 WA policy change's effective date consequently traveled many fewer miles to their chosen dialysis center, were more likely to be treated at a dialysis center in their own county, and were treated at centers with more stations-per-patient, nurses-per-patient, and dieticians-per-patient. Figures 3-10 plot the event studies associated with these estimates. There is little evidence of pretrends for all outcomes except nurses-per-patient. See the discussion near page 23. Data source(s): USRDS.

	(1)	(2)	(3)	(4)	(5)	(6)
	1[Home HD]	1[Home PD]	1[Any Hosp.]	1[Hosp. For Cardio. Event]	1[Hosp. For Infec.]	1[Death]
1[Center In County]	-0.0747**	-0.0888	-0.0691***	-0.0596**	-0.0240**	-0.0009
	(0.0360)	(0.0544)	(0.0255)	(0.0247)	(0.0096)	(0.0038)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$
Window (Yrs.)	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$
T. ZCTAs	94	94	87	87	87	94
C. ZCTAs	921	921	882	882	882	921
B-line Y	0.033	0.129	0.123	0.114	0.043	0.012
F-Stat.	16.0	16.0	13.9	13.9	13.9	16.0
N	309,225	309,225	218,142	218,142	218,142	309,225
Clusters	219	219	218	218	218	219
Adj. R^2	-0.005	0.005	-0.003	-0.003	-0.002	-0.000

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 16. These tables reports estimates of β from equation (7). Under the IV-DID assumptions discussed in the main text, it shows that patients in the target WA counties that experienced their first dialysis center opening after the 2007 WA policy change's effective date consequently used less HHD, were less likely to be hospitalized in a given month for any reason, were less likely to be hospitalized in a given month for a cardiovascular-related event, and were less likely to be hospitalized for an infection. They were not statistically significantly less likely at the 95% level to use PD or die. Figures 3-10 plot the event studies associated with these estimates. There is little evidence of pretrends for all outcomes except PD and hospitalizations for an infection. See the discussion near page 23. Data source(s): USRDS.

	(1) Miles to Chosen Center	(2) 1[Treated In Own County]	(3) Stations Per Patient At Chosen Center	(4) Nurses Per Patient At Chosen Center	(5) Diets. Per Patient At Chosen Center	(6) PCTs Per Patient At Chosen Center
1[Center In County]	-8.0844***	0.6232***	0.0850***	0.0244***	0.0071***	0.0031
	(1.0862)	(0.0382)	(0.0204)	(0.0058)	(0.0007)	(0.0055)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	[1993, 2015]	[1993, 2015]	[1993, 2015]	[2005, 2015]	[2005, 2015]	[2005, 2015]
Window (Yrs.)	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$
T. ZCTAs	51	51	51	6	6	6
C. ZCTAs	1,040	1,041	1,040	710	710	710
B-line Y	18.811	0.000	0.256	0.052	0.010	0.095
F-Stat.	62.8	63.4	63.5	262.1	262.1	262.1
N	3,692,043	3,763,287	3,732,737	790,763	790,763	790,763
Clusters	224	224	224	159	159	159
Adj. R^2	0.016	0.342	0.016	0.001	0.006	-0.001

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 17. This table reports estimates of β from equation (10). Under the IV-DID assumptions discussed in the main text, it shows that patients in the threshold-crossing NC counties that experienced their first dialysis center opening after their counties' threshold-crossings' effective dates consequently traveled many fewer miles to their chosen dialysis center, were more likely to be treated at a dialysis center in their own county, and were treated at dialysis centers with more stations-per-patient, nurses-per-patient, and dieticians-per-patient. Figures 3-10 plot the event studies associated with these estimates. There is little evidence pretrends for any of these outcomes. See the discussion near page 23. Data source(s): USRDS.

	(1)	(2)	(3)	(4)	(5)	(6)
	1[Home HD]	1[Home PD]	1[Any Hosp.]	1[Hosp. For Cardio. Event]	1[Hosp. For Infec.]	1[Death]
1[Center In County]	-0.0131**	-0.0875**	-0.0124	-0.0162	-0.0124	0.0020
	(0.0066)	(0.0400)	(0.0125)	(0.0117)	(0.0079)	(0.0033)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	Y	Y	Y	Y	Y	Y
Pat. Char.	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	[1993, 2015]	[1993, 2015]	[1993, 2015]	[1993, 2015]	[1993, 2015]	[1993, 2015]
Window (Yrs.)	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$
T. ZCTAs	51	51	51	51	51	51
C. ZCTAs	1,042	1,042	1,034	1,034	1,034	1,042
B-line Y	0.005	0.149	0.166	0.159	0.071	0.019
F-Stat.	62.7	62.7	54.0	54.0	54.0	62.7
N	3,823,506	3,823,506	3,090,919	3,090,919	3,090,919	3,823,506
Clusters	224	224	224	224	224	224
Adj. R^2	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 18. This table reports estimates of β from equation (10). Under the IV-DID assumptions discussed in the main text, it shows that patients in the threshold-crossing NC counties that experienced their first dialysis center opening after their counties' threshold-crossings' effective dates consequently used less HHD and less PD. They were not statistically significantly less likely to experience hospitalizations or die. Figures 3-10 plot the event studies associated with these estimates. There is little evidence of pretrends for all outcomes except mortality. See the discussion near page 23. Data source(s): USRDS.

	(1) Expected Utility (Miles-Traveled Equivalents)
1[Center In County]	14.3140***
	(4.5284)
Month FE	Y
Region Char.	Y
Pat. Char.	Y
ZCTA FE	Y
Yr. Range	$[2000, 2015]$
Window (Yrs.)	$[-8, 6]$
T. ZCTAs	88
C. ZCTAs	848
B-line Y	-50.089
F-Stat.	16.9
N	296,136
Clusters	218
Adj. R^2	0.296

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 19. This table reports estimates of β from equation (7) for the expected utility outcome introduced in section III.C. Under the IV-DID assumptions discussed in the main text, it shows that patients in the target WA counties that experienced their first dialysis center opening after the 2007 WA policy change's effective date consequently experienced higher expected utility. See the discussion near page 25. Data source(s): USRDS.

	(1) Expected Utility (Miles-Traveled Equivalents)
1[Center In County]	11.4616***
	(1.2749)
Month FE	Y
Region Char.	Y
Pat. Char.	Y
ZCTA FE	Y
Yr. Range	$[1993, 2015]$
Window (Yrs.)	$[-5, 4]$
T. ZCTAs	51
C. ZCTAs	1,029
B-line Y	-73.146
F-Stat.	63.6
N	3,794,093
Clusters	224
Adj. R^2	0.243

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. 20. This table reports estimates of β from equation (10) for the expected utility outcome introduced in section III.C. Under the IV-DID assumptions discussed in the main text, it shows that patients in the threshold-crossing NC counties that experienced their first dialysis center opening after their counties' threshold-crossings' effective dates consequently experienced higher expected utility. See the discussion near page 25. Data source(s): USRDS.

Back-of-the-envelope welfare calculations

For the dialysis center openings that followed the 2007 WA policy change and patients living in the target WA counties

A. Patient surplus from revealed preferences

(1)	Patient surplus gain per one-way trip among compliers **(MTE)**:	14.31
(2)	Number of one-way trips per complier patient-month:	24
(3)	Patient surplus gain per complier patient-month **(MTE)**: [=(1)*(2)]	344
(4)	Number of complier patient-months per patient-month:	0.422
(5)	Patient surplus gain per patient-month **(MTE)**: [=(3)*(4)]	145
(6)	Average number of patient-months per county-month:	14.6
(7)	Patient surplus gain per county-month **(MTE)**: [=(5)*(6)]	2,122
(8)	Number of complier county-months per county-month:	0.204
(9)	Patient surplus gain per complier county-month **(MTE)**: [=(7)/(8)]	**10,422**

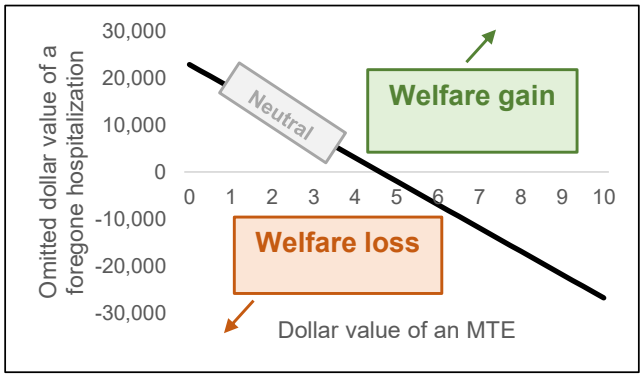
B. Fixed costs

(10)	Fixed cost gain per complier county-month **(dollars)**:	**47,969**

C. Hospitalization rates

(11)	Change in the probability of a hospitalization per complier patient-month (percentage points):	-6.91
(12)	Change in the number of hospitalizations per complier county-month: [=(11)*(4)*(6)/(100*(8))]	**-2.10**

D. Welfare neutral condition



Tab. 21. Panel (A) aggregates the marginal centers' contributions to expected utility to the county level. Row (1) is the estimate reported in table 19. Row (4) is the patient-weighted first stage. (I.e., the estimate of δ in equation (6).) Row (6) is the average number of dialysis patients among the target WA counties after the 2007 WA policy change and within the estimation window reported in table 19. Row (8) is the estimate reported in table 13. See the discussion near page 25. Panel (B) reports the marginal centers' estimated county-level fixed cost contribution. Row (10) is the estimate reported in table A2. See the discussion near page 26. Panel (C) aggregates the marginal centers' contributions to lower hospitalization rates to the county level. Row (11) is the estimate reported in table table 16. See the discussion near page 24. Finally, panel (D) plots $\kappa_2 = \frac{48{,}000-10{,}500\kappa_1}{2.1}$, as discussed near page 27. Data source(s): USRDS and HCRIS.

Back-of-the-envelope welfare calculations

For the dialysis center openings that followed the NC threshold-crossings and patients living in the threshold-crossing counties

A. Patient surplus estimates (choice data)

(1)	Patient surplus gain per one-way trip among compliers **(MTE)**:	11.46
(2)	Number of one-way trips per complier patient-month:	24
(3)	Patient surplus gain per complier patient-month **(MTE)**: [=(1)*(2)]	275
(4)	Number of complier patient-months per patient-month:	0.608
(5)	Patient surplus gain per patient-month **(MTE)**: [=(3)*(4)]	167
(6)	Average number of patient-months per county-month:	35.7
(7)	Patient surplus gain per county-month **(MTE)**: [=(5)*(6)]	5,979
(8)	Number of complier county-months per county-month:	0.566
(9)	Patient surplus gain per complier county-month **(MTE)**: [=(7)/(8)]	**10,557**

B. Fixed cost estimates

(10)	Fixed cost gain per complier county-month **(dollars)**:	**35,328**

C. Hospitalization rate estimates

(11)	Change in the probability of a hospitalization per complier patient-month (percentage points):	0.00
(12)	Change in the number of hospitalizations per complier county-month: [=(11)*(4)*(6)/(100*(8))	**0.00**

D. Welfare neutral condition

(13)	Dollars per MTE required to equilibrate patient surplus gains with fixed costs: [=(10)/(9)]	**3.35**

Tab. 22. Panel (A) aggregates the marginal centers' contributions to expected utility to the county level. Row (1) is the estimate reported in table 20. Row (4) is the patient-weighted first stage. (I.e., the estimate of δ in equation (9).) Row (6) is the average number of dialysis patients among the threshold-crossing NC counties after their threshold-crossings' effective dates and within the estimation window reported in table 20. Row (8) is the estimate reported in table 14. See the discussion near page 25. Panel (B) reports the marginal centers' estimated county-level fixed cost contribution. Row (10) is the estimate reported in table A3. See the discussion near page 26. Panel (C) aggregates the marginal centers' contributions to lower hospitalization rates to the county level. This is set to zero because I cannot reject the null hypothesis that the marginal centers did not affect patients' hospitalization rates. See table 18 and the discussion near page 24. Finally, panel (D) reports the value of κ_1 necessary to equilibrate the marginal centers' contributions to patient surplus in panel (A) with their fixed cost contribution in panel (B), as discussed near page 27. Data source(s): USRDS and HCRIS.

	(1) Competitors In 10 Mi.	(2) Miles To Nearest Competitor	(3) Stations Per Patient	(4) Nurses Per Patient	(5) Dieticians Per Patient	(6) PCTs Per Patient
1[CON]	-2.085***	4.498***	-0.047***	-0.030***	-0.004***	0.018***
	(0.367)	(1.294)	(0.009)	(0.003)	(0.001)	(0.002)
Year FE	Y	Y	Y	Y	Y	Y
County Char.	Y	Y	Y	Y	Y	Y
Est. Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
$\hat{Y}\|X = 0$	4.522	7.977	0.357	0.087	0.016	0.078
N	10,835	10,835	10,426	10,435	10,435	10,435
Clusters	376	376	376	376	376	376
Adj. R^2	0.606	0.316	0.025	0.040	0.033	0.040

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. 23. This table reports my estimates of β in equation (1). They are computed from a sample of center-years spanning 2005 to 2016 in North Carolina, South Carolina, Georgia, Tennessee, and Virginia. (The latter four states did not have a dialysis CON program between 2005 and 2016.) It shows that NC dialysis centers had fewer competitors nearby, were farther from their nearest competitor, had fewer stations-per-patient, nurses-per-patient, and technicians-per-patient, but had more PCTs-per-patient. See the discussion near page 29. Data source(s): USRDS.

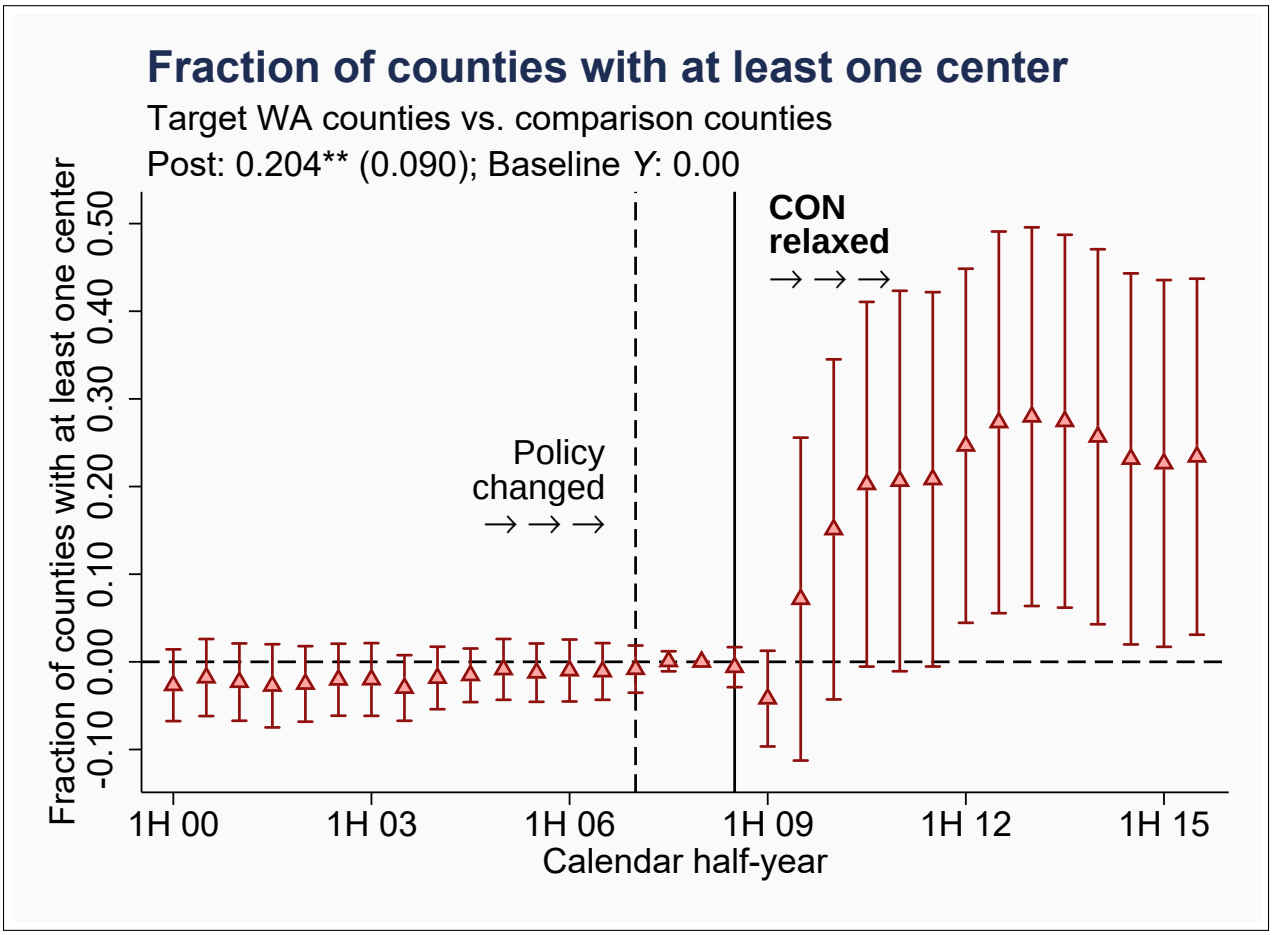


Fig. 1. This figure plots estimates of $(\beta_l : l \in \mathcal{L})$ in equation (3) and their 95% confidence intervals. The figure heading reports the corresponding estimate of β in equation (2) and baseline average value of the outcome. (Note that the comparison counties are other counties in the region that did not have a dialysis center prior to the 2007 WA policy change's effective date.) The figure shows that the likelihood of having at least one dialysis center grew more in the target WA counties after the 2007 WA policy change's effective date than it grew in the WA comparison counties contemporaneously. See the discussion near page 21. Data source(s): USRDS.

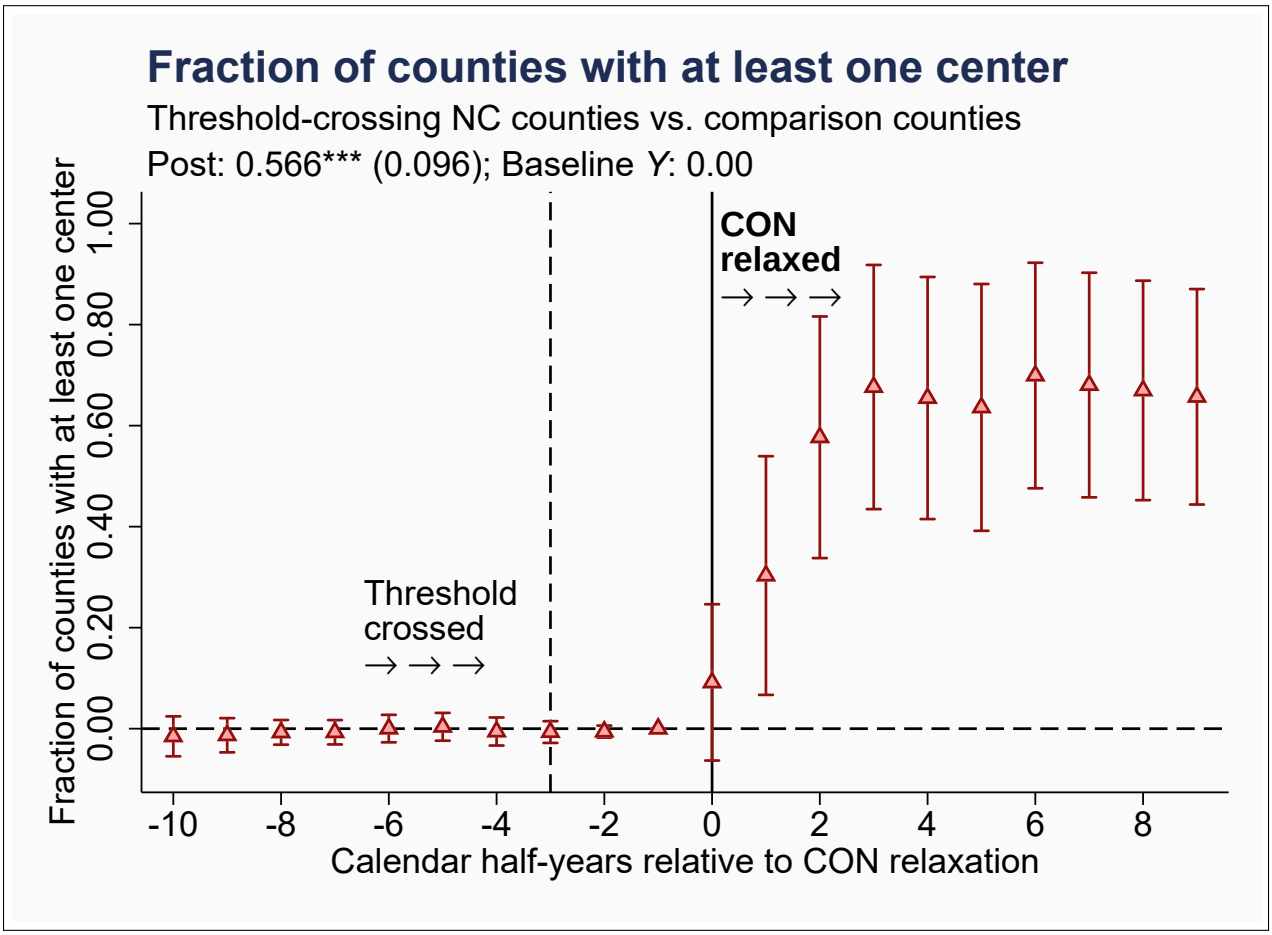


Fig. 2. This figure plots estimates of $(\beta_l : l \in \mathcal{L})$ in equation (5) and their 95% confidence intervals. The figure heading reports the corresponding estimate of β in equation (4) and baseline average value of the outcome. (Note that the comparison counties selected for each threshold-crossing event are other counties in the region that did not have a dialysis center prior to the threshold-crossings' effective dates.) The figure shows that the likelihood of having at least one dialysis center grew more in the threshold-crossing NC counties after their threshold-crossings' effective dates than it grew in the NC comparison counties contemporaneously. See the discussion near page 21. Data source(s): USRDS.

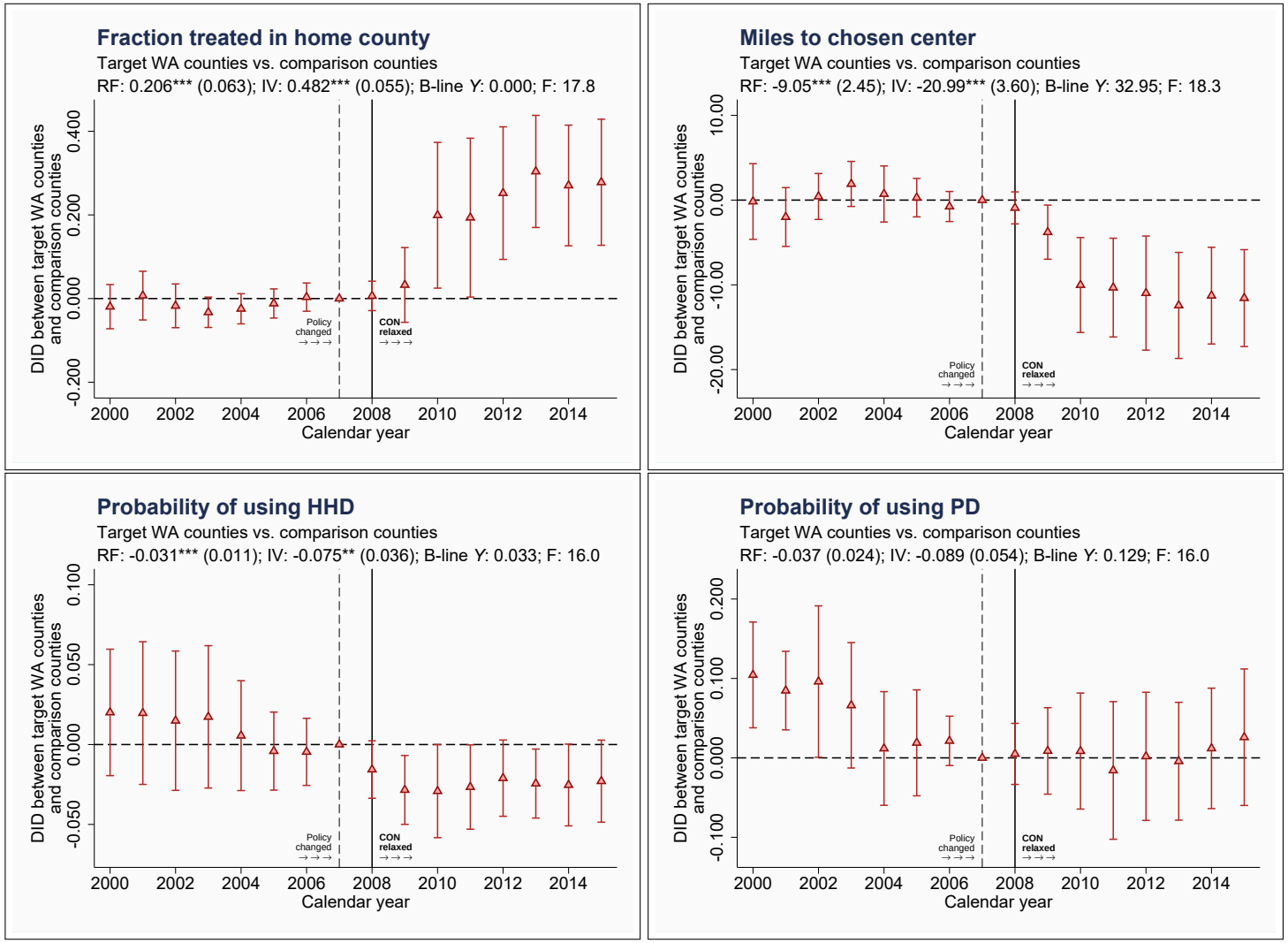


Fig. 3. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for various access-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

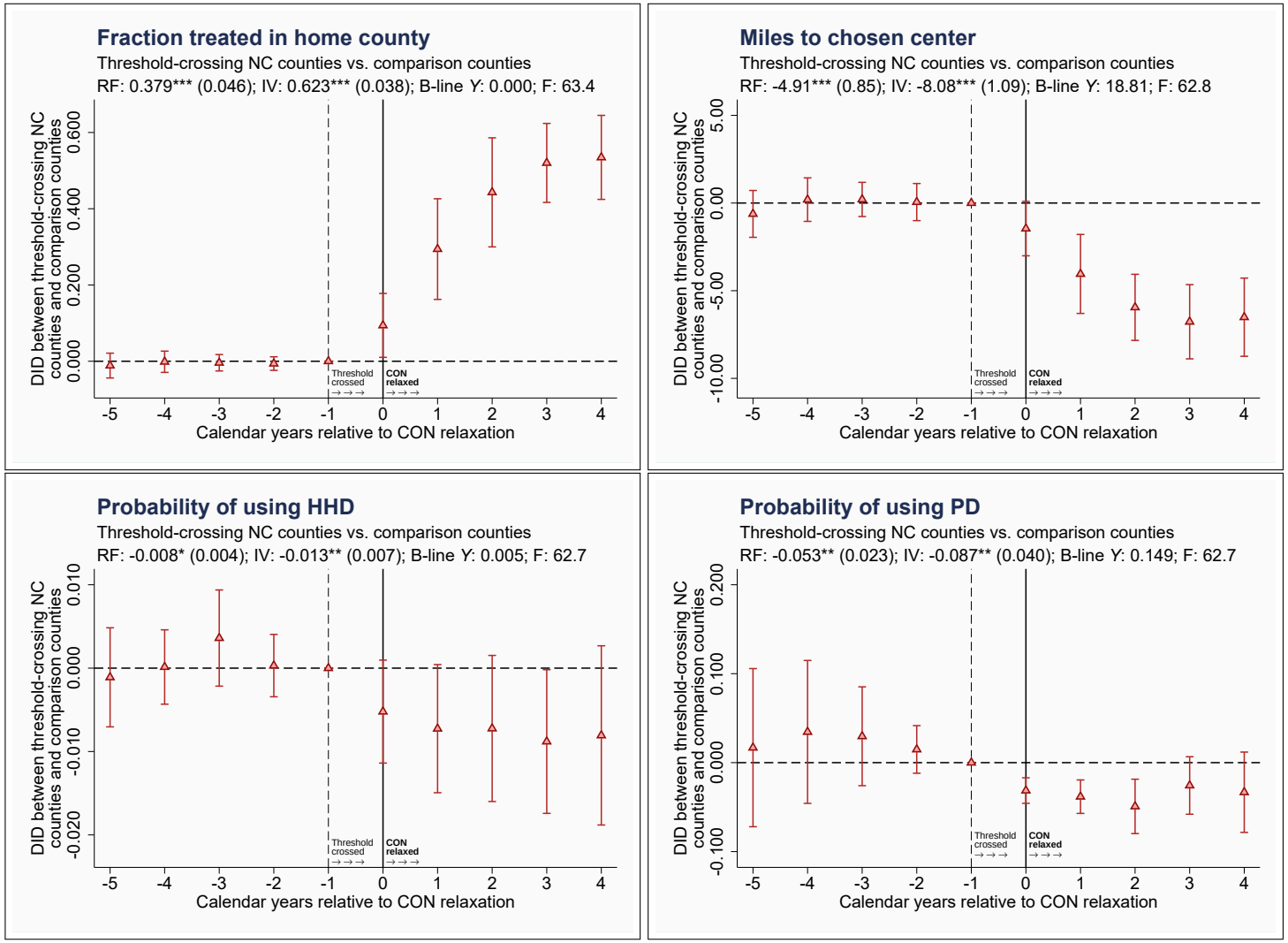


Fig. 4. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for various access-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

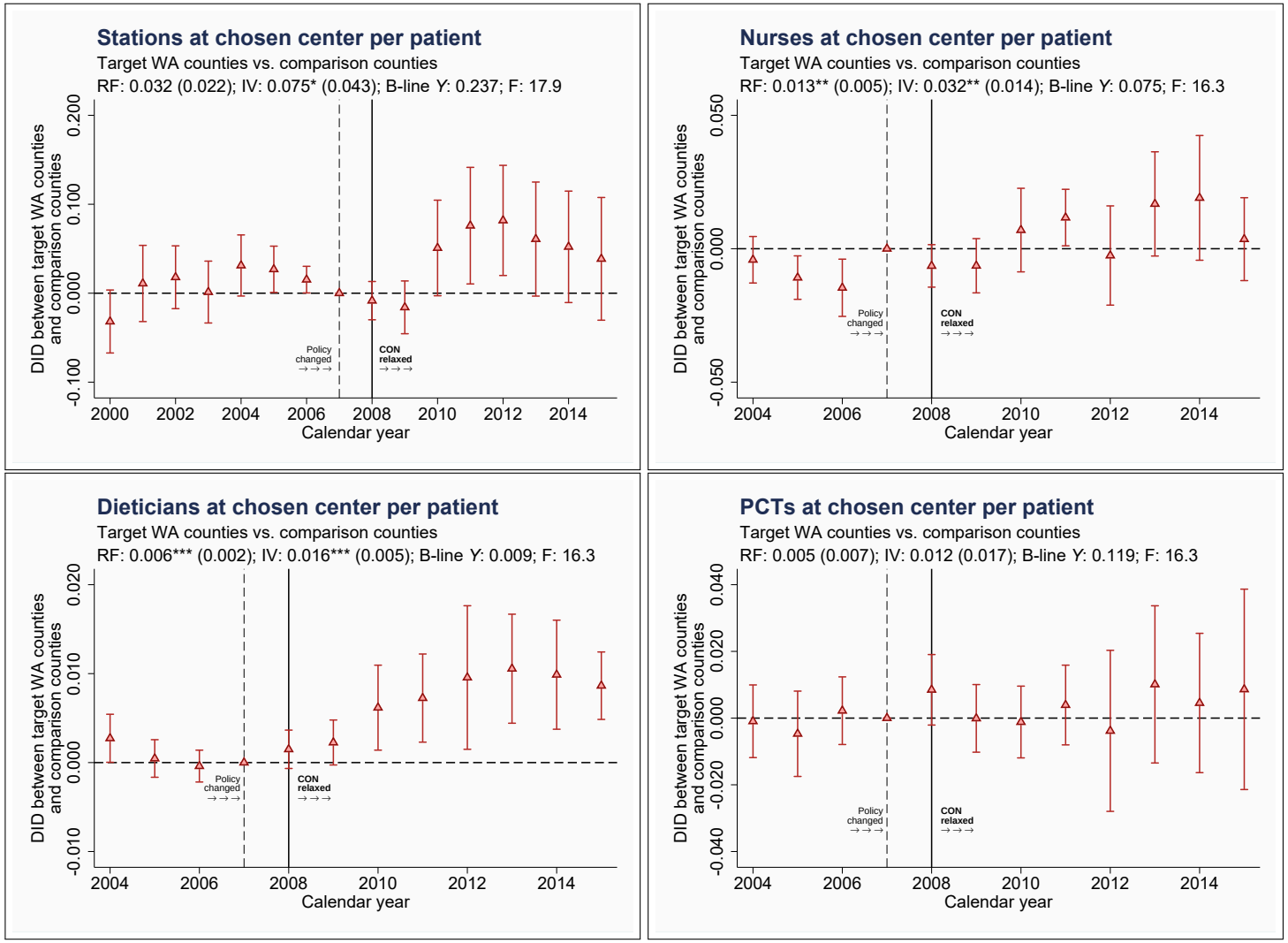


Fig. 5. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for various resource-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

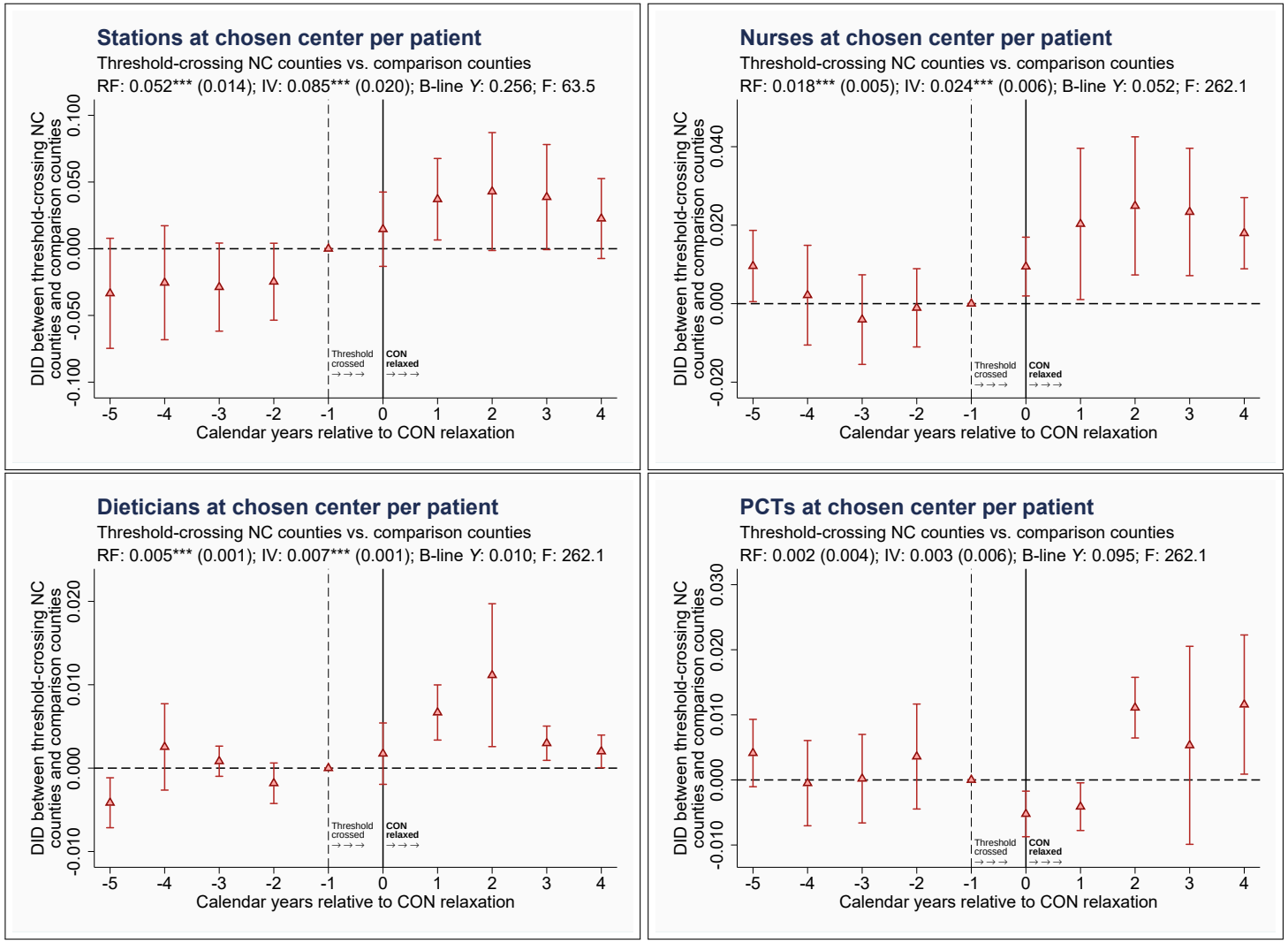


Fig. 6. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for various resource-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

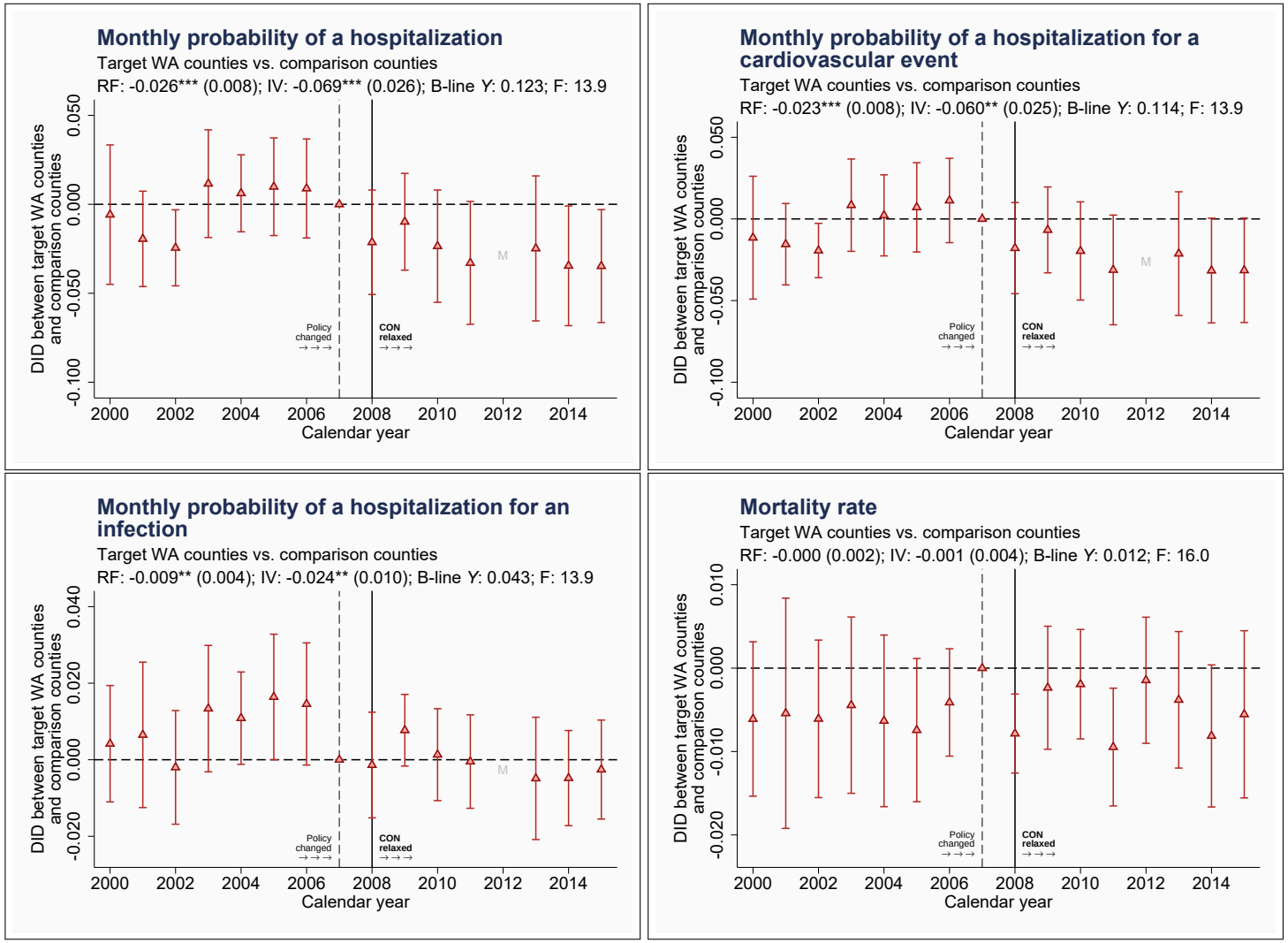


Fig. 7. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for various health-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

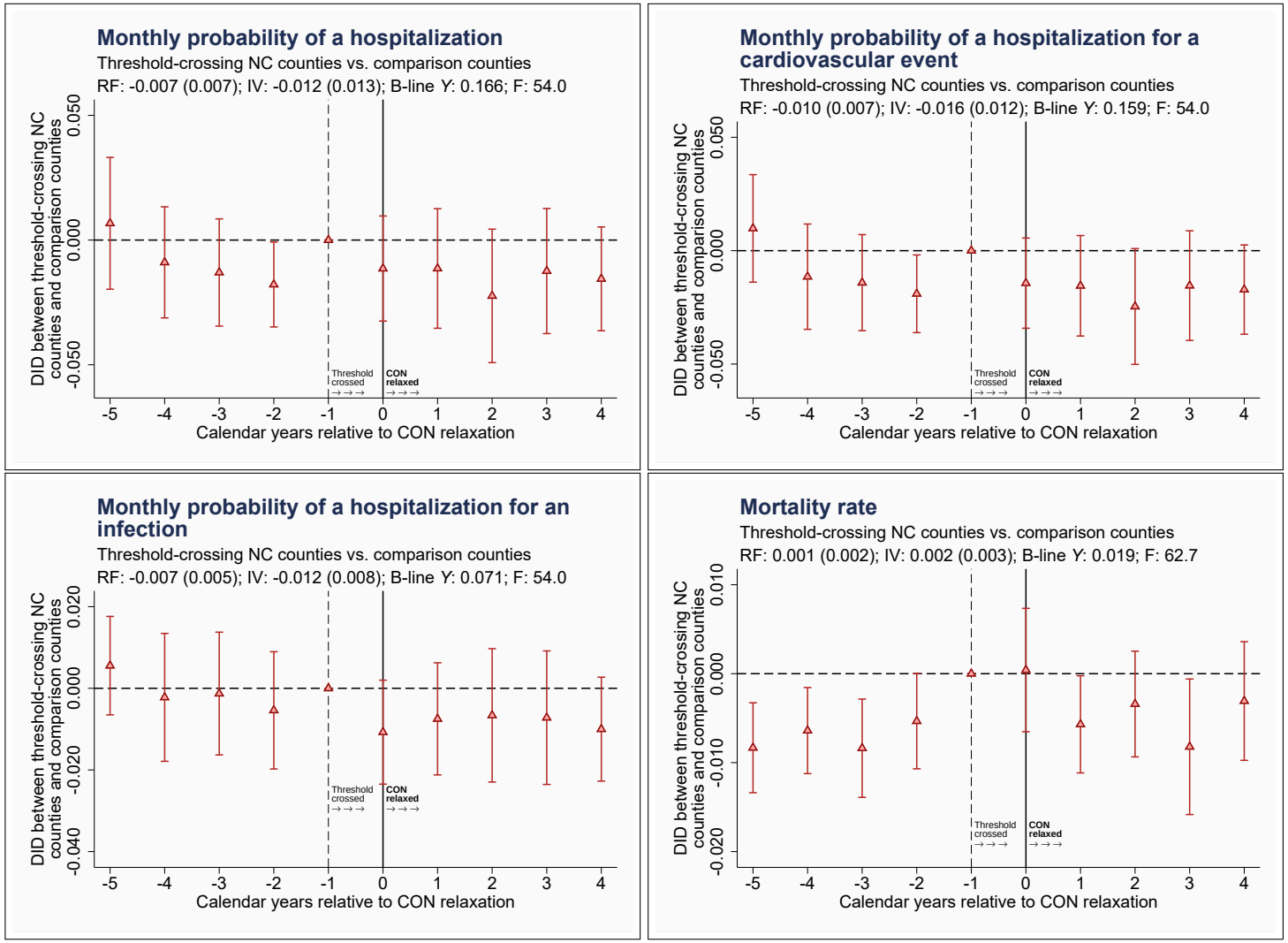


Fig. 8. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for various health-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

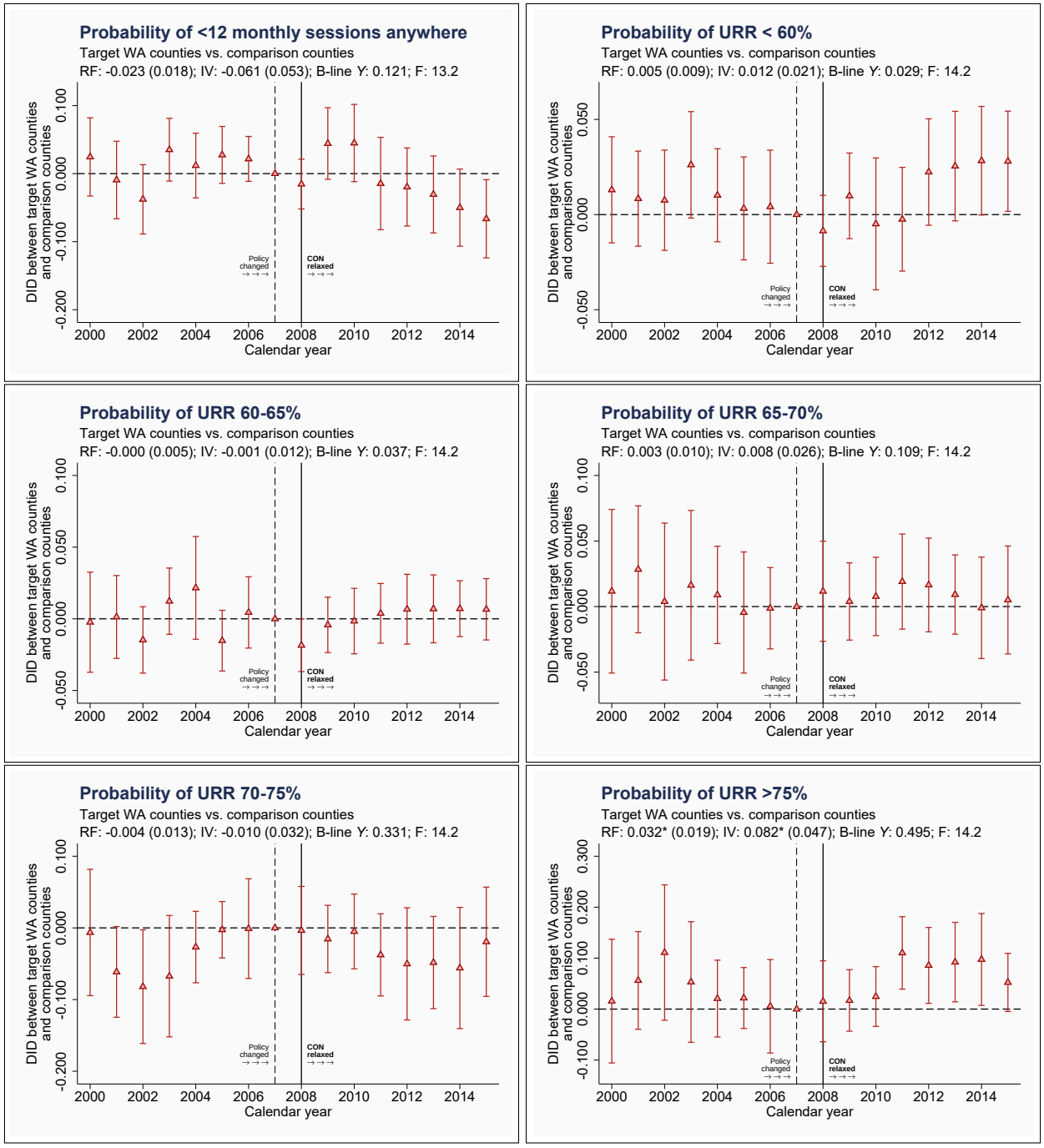


Fig. 9. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for various dialysis adequacy-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

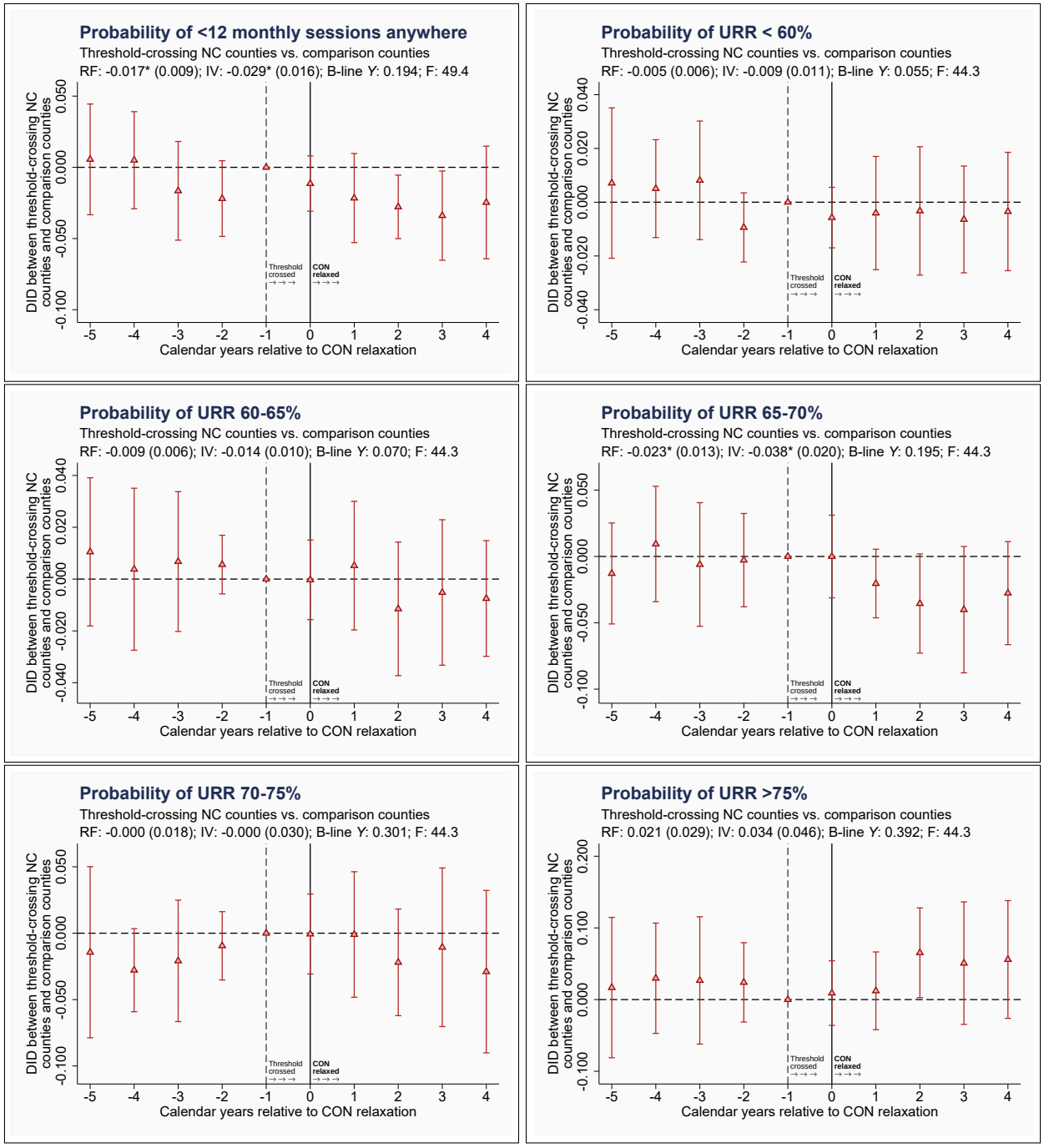


Fig. 10. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for various dialysis adequacy-related outcomes. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 24. Data source(s): USRDS.

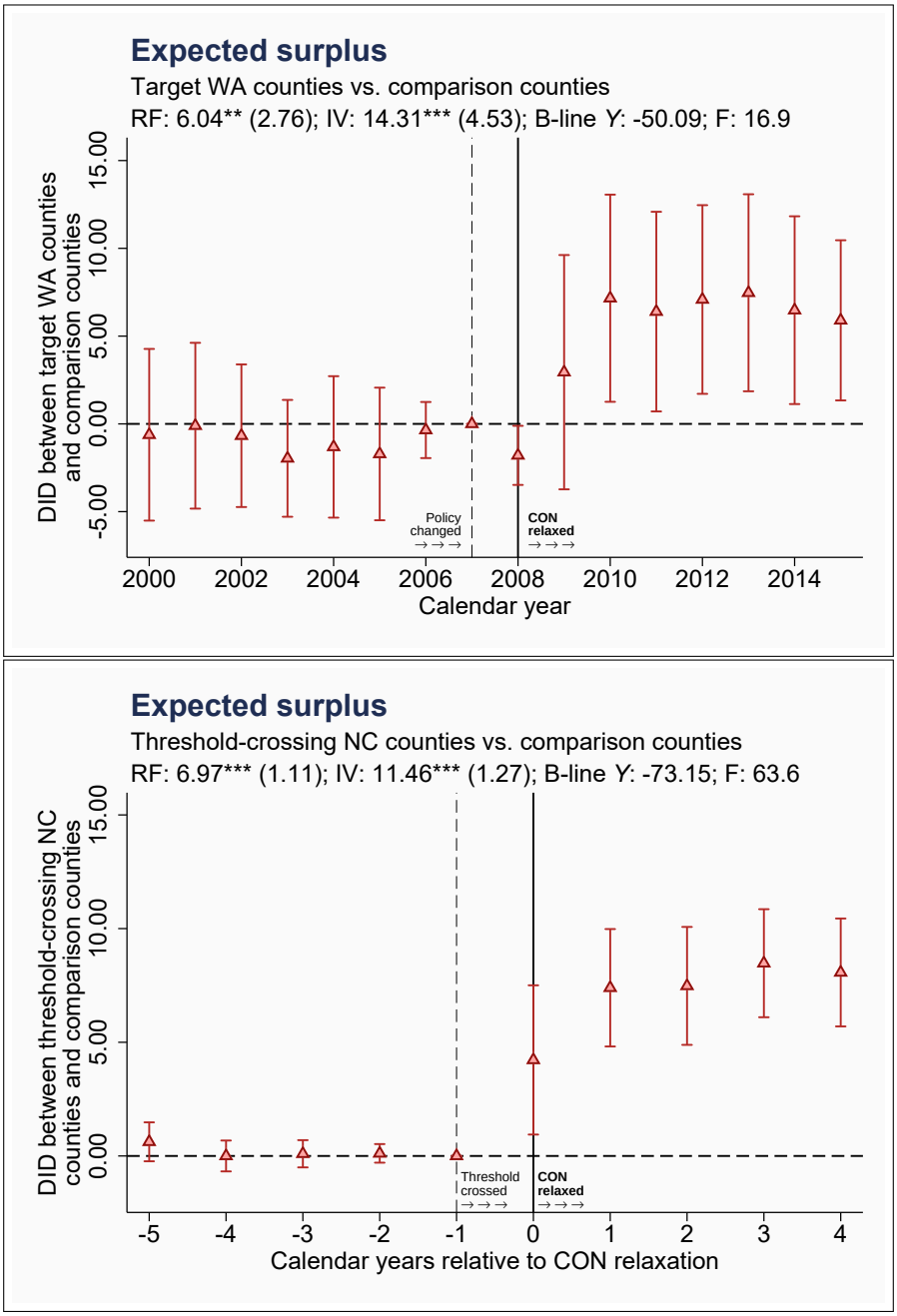


Fig. 11. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equations (8) and (11) and their 95% confidence intervals for the expected utility outcome introduced in section III.C. The figure headings report the corresponding estimates from the static analogues of equations (8) and (11), the IV-DID estimates from equations (7) and (10), the baseline average values of the outcome, and the first-stage F-statistics. See the discussion near page 25. Data source(s): USRDS.

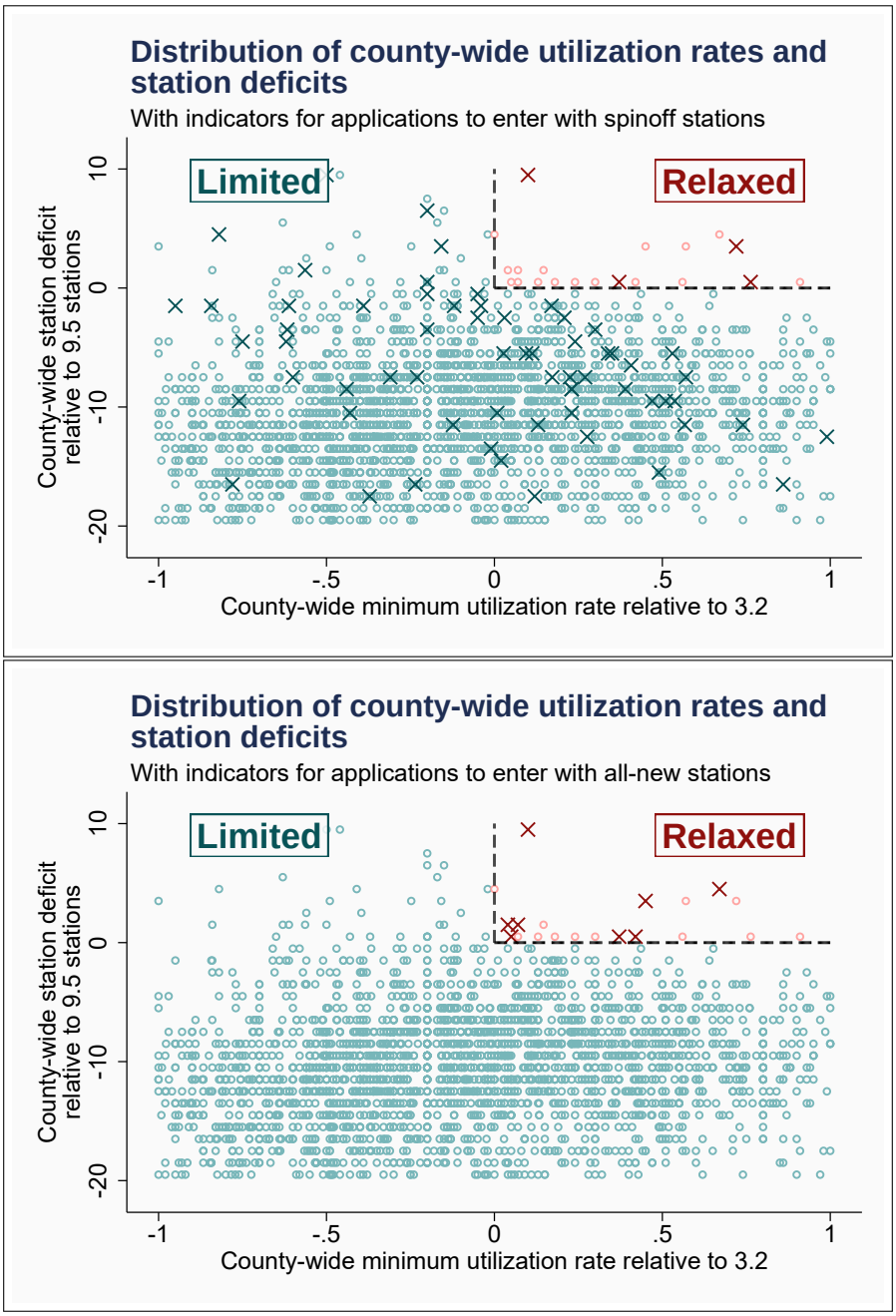


Fig. 12. These figures plot for NC counties with at least one dialysis center the joint distribution of their semiannual dialysis station deficits and countywide minimum utilization rates. Panel (a) indicates with an × county-half-years in which an application to open a new dialysis center using at least some existing dialysis stations was filed and subsequently approved. Panel (b) indicates with an × county-half-years in which an application to open a new dialysis center without using any existing dialysis stations was filed and subsequently approved. (One such county-half-year lies outside the range of the figure in the limited area.) See the discussions near page 28. Data source(s): NC dialysis CON program.

Appendices

A. Were the 2007 WA policy change and the NC threshold-crossings really linked to subsequent entry?

In section III.A, I showed that dialysis centers opened in the affected counties after their events' effective dates more quickly than in the WA and NC comparison counties contemporaneously. In this section, I report supplemental evidence to strengthen the conceptual link between the events and the affected counties' subsequent entries.

In Washington, I investigate whether the dialysis centers that opened in the target WA counties after the 2007 WA policy change were "too big" to open under the pre-2007 rules and "small enough" to open under the post-2007 rules. Table A4 presents my findings. In panel (A) columns (2)-(7), it reports the target WA counties' patient populations at various times between 2006 and 2015. In panel (B) columns (2)-(7), it reports the sum of the target WA counties' patient populations and the patient populations of those adjacent counties that did not have dialysis centers. Both panels report the opening dates and capacities of the five dialysis centers that opened in a target WA county after the 2007 WA policy change in columns (8)-(10). Finally, in column (11) of panels (A) and (B), the table reports the number of projected resident in-center dialysis patients needed to justify each dialysis center's capacity under the 4.8 patients-per-station or 3.2 patients-per-station rule, respectively. I observe that most values in panel (A) column (11) are much larger than values in panel (A) columns (2)-(7), suggesting that these five dialysis centers might not have been able to open around those dates with those capacities under the pre-2007 policy. I also observe that most values in Panel (B) column (11) are much closer to values in Panel (B) columns (2)-(7), and in most cases lower. These data support the view that the 2007 WA policy change was responsible for spurring entries in the target WA counties.[40]

In North Carolina, I investigate whether providers promptly filed applications to open new dialysis centers in response to announcements published in SDRs that a planning area had experienced a threshold-crossing. I examine whether the 24 planning areas that had zero dialysis centers as of March 1997 had higher application filing rates when their projected station deficits were 9.5

[40]There are two caveats to this inference. First, the WA dialysis CON program would have used projected patient populations to make its determinations. The table reports actual patient populations, though these may be adequate proxies. Second, the entrants could have in theory applied to open with fewer dialysis stations but for the policy change. However, panel (A) columns (2)-(7) suggest that they would have had to open somewhere in the range of 2-6 stations. In figure A4, I plot the joint distribution of stations and patients-per-station among dialysis centers in Washington and other Western states in 2006. This figure shows that it was relatively rare for dialysis centers to have fewer than 6 stations, and it almost never happened that they had fewer than 6 stations and more than 4.8 patients-per-station.

stations or more. Since these 24 planning areas were all counties, I refer to them as counties hereafter.[41] Since counties with high projected station deficits mechanically have high projected patient populations, I examine application filing rates very close to the NC deficit threshold to separate the effect of having a large projected patient population from the effect of being above the NC deficit threshold *per se*. In theory, if the NC deficit threshold was binding, then we would expect to see a discontinuity around the NC deficit threshold in the application filing rate.

Figure A3 illustrates the relationship between a planning area's projected station deficit, the NC deficit threshold, and application filing rates in the foregoing 24 counties. The figure plots each county's projected station deficit against the NC deficit threshold. Thirteen counties experienced a threshold-crossing. In most of these thirteen counties, providers filed successful applications to open new dialysis centers immediately.[42][43] Eleven counties never experienced a threshold-crossing. In all but three of these eleven counties, no providers ever filed successful applications to open new dialysis centers. Overall, this figure suggests that when the 24 counties experienced a threshold-crossing, providers were much more likely to file successful applications to open new dialysis centers.

I use regression discontinuity design ("RDD," hereafter) methods to measure the size of the discontinuity in the application filing rate around the NC deficit threshold. I organize my data into a county-half year panel. The counties are the 24 counties in figure A3. For each county, I include all half years between 1997 and 2019 in which that county did not yet have a dialysis center. Mathematically, let i index counties and let t index half years. For each county i in each half year t, I observe the number c_{it} of dialysis stations operating at 3.2 patients-per-station that the NC dialysis CON program reported would be needed to serve the county's projected resident in-center patient population. The NC deficit threshold was triggered when $c_{it} \geq 9.5$. Define $\tilde{c}_{it} := c_{it} - 9.5$.

[41] The 24 counties are reported in figure A3 below. I exclude Carteret, Caswell, and Dare counties from this group. Although they did not have dialysis centers in March 1997, applications had already been filed to establish dialysis centers in these counties. The projects associated with those applications were completed soon after March 1997.

[42] Polk County had an approved application already on file in March 1997. This application filing is not shown because it occurred in December 1996, before the start of my sample period. It did not reduce the March 1997 projected station deficit because it was reported to have been denied in February 1997. Despite this report, a certificate of need was issued to the applicant in August 1997. The project was not completed and the certificate of need was withdrawn by March 1999. Another application was filed in the first half of 2007 by another applicant after Polk County was reported to have a projected station deficit of at least 9.5 stations. This application was denied. It is the only pictured application filing that occurred while a county had a projected station deficit of at least 9.5 stations that was denied. The same applicant filed a new application at the next opportunity. This application was approved, but the project was not completed.

[43] Among these thirteen counties, three counties (Davie, Jones, and Washington) experienced application filings before they experienced a threshold-crossing. Those applications were not approved.

I estimate the model:

$$Y_{it} = \beta \mathbb{1}[\tilde{c}_{it} \geq 0] + \delta_1 \tilde{c}_{it} + \delta_2 \tilde{c}_{it} \mathbb{1}[\tilde{c}_{it} \geq 0] + \varepsilon_{it} \tag{15}$$

where Y_{it} indicates that an application to open a new dialysis center had been filed in half year t. I estimate β using mean squared error optimal bandwidths and compute robust confidence intervals, as in Calonico et al. (2014a) and Calonico et al. (2014b).

Table A5 reports my estimate of β.[44] Figure A5 plots the relationship between $\tilde{c}_{it}$ and Y_{it} around $\tilde{c}_{it} = 0$. I find that when a NC county with zero dialysis centers experienced a threshold-crossing, an application to open a new dialysis center was filed 69.1 percentage points more often than otherwise. My estimate of β suggests that the NC deficit threshold was a binding restraint on applications for dialysis center openings in counties with zero dialysis centers. In other words, it suggests that when counties crossed the NC deficit threshold, providers experienced a discontinuous entry cost shock spurring them to file applications to open new dialysis centers.

B. Are the IV-DID estimates robust to changes in the composition of the underlying patient populations?

In section III.B, I reported IV-DID estimates that relied on ZCTA-level fixed effects. Consequently, the estimates may be biased by compositional changes in the underlying patient populations. While I cannot reject the possibility that unobserved patient characteristics systematically changed in tandem with the 2007 WA policy change and the NC threshold-crossings, I may examine whether my results are robust to changes in the mix observable patient characteristics. To do so, I use the observable patient characteristics to predict the outcomes discussed in section III.B. Then, I treat the predicted outcomes as outcomes and estimate equations (6)-(11) (excluding the ΓX terms).

Tables A6 and A7 summarize the results for the WA analysis. Tables A8 and A9 summarize the result for the NC analysis. In both sets of results, the estimates are generally small relative to the estimates reported in the main text and not statistically significantly different from zero at the 95% level. Figures A6-A13 plot the corresponding event studies.

[44] It also reports the robust McCrary test statistic and p-value (Cattaneo et al., 2018). I do not find evidence of manipulation of the running variable.

	(1) Ln(Fixed Costs)
At-home Patients	0.0092***
	(0.0004)
(At-home Patients)^2	-0.0000***
	(0.0000)
Incenter Patients	0.0119***
	(0.0004)
(Incenter Patients)^2	-0.0000***
	(0.0000)
Stations	0.0250***
	(0.0021)
Incenter Patients× Stations	-0.0001***
	(0.0000)
1[Freestanding]	0.6725
	(0.6123)
County Rurality	-0.1528***
	(0.0194)
State FE	Y
Chain-by-trend FE	Y
Age FE	Y
N	34,341
Clusters	5,618
Adj. R^2	0.713

SEs clustered at facility-level in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. A1. This table reports estimates of equation (12). See the discussion near page 26. Data source(s): USRDS and HCRIS.

	(1) Monthly fixed costs
Has Center	47969.325***
	(6911.211)
Month FE	Y
County FE	Y
Pat. Pop. Chars.	Y
Window	[2000, 2015]
T. Units	14
C. Units	207
Baseline Y	0.00
N	42,431
Clusters	221
Adj. R^2	0.66

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. A2. This table reports estimates of β from equation (7) for the county-level fixed cost outcome described in section III.D. See the discussion near page 26. Data source(s): USRDS and HCRIS.

	(1) Monthly fixed costs
Has Center	35328.310***
	(3150.808)
Month FE	Y
County FE	Y
Pat. Pop. Chars.	Y
Window	[1993, 2015]
T. Units	12
C. Units	225
Baseline Y	0.00
N	202,645
Clusters	226
Adj. R^2	0.74

County-level cluster-robust SEs in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Tab. A3. This table reports estimates of β from equation (10) for the county-level fixed cost outcome described in section III.D. See the discussion near page 26. Data source(s): USRDS and HCRIS.

Patient populations and new center characteristics

In the target WA counties

(A) Before the 2007 WA policy change

County Name	Resident In-Center Patient Populations Contributing To Need (Own-County Only)							New Center Characteristics			Projected Patients Needed to Meet 4.8 Patients-Per-Station Threshold
	2006	2007	2008	2009	2010	2012	2015	Opening Date (Range)	Stations (Range) Starting	Stations (Range) 2 Yr. Max	
(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11) =(9)*4.8
1. Stevens	12	12	14	19	25	28	36	Jun. 2009	10	10	48
2. Adams	11	16	17	16	18	18	19	Jul. 2009	5	8	24
3. Pacific	23	22	22	24	23	16	23	Jan. 2010	10	10	48
4. Jefferson	13	13	<11	<11	<11	15	18	Sep. 2010	6	6	29
5. Douglas	29	34	36	31	30	33	31	Mar. 2012	8	8	38
6. Pend Oreille	<11	11	15	15	<11	14	15	-	-	-	-
7. Klickitat	12	12	14	12	13	13	15	-	-	-	-
8. Lincoln	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
9. Ferry	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
10. Skamania	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
11. Wahkiakum	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
12. San Juan	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
13. Garfield	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
14. Columbia	<11	<11	<11	<11	<11	<11	<11	-	-	-	-

(B) After the 2007 WA policy change

County Name	Resident In-Center Patient Populations Contributing To Need (Own County + Neighboring County Without Center)							New Center Characteristics			Projected Patients Needed to Meet 3.2 Patients-Per-Station Threshold
	2006	2007	2008	2009	2010	2012	2015	Opening Date	Stations (Range) Starting	Stations (Range) 2 Yr. Max	
(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11) =(9)*3.2
1. Stevens	31	30	35	43	39	49	67	Jun. 2009	10	10	32
2. Adams	19	21	22	22	22	21	28	Jul. 2009	5	8	16
3. Pacific	28	28	25	28	27	21	27	Jan. 2010	10	10	32
4. Jefferson	13	13	<11	<11	12	15	20	Sep. 2010	6	6	19
5. Douglas	29	34	36	31	30	33	31	Mar. 2012	8	8	26
6. Pend Oreille	20	23	29	23	<11	14	15	-	-	-	-
7. Klickitat	17	18	21	19	18	20	18	-	-	-	-
8. Lincoln	33	35	38	24	<11	<11	15	-	-	-	-
9. Ferry	22	19	21	16	<11	<11	15	-	-	-	-
10. Skamania	17	18	21	19	18	20	18	-	-	-	-
11. Wahkiakum	28	28	25	28	<11	<11	<11	-	-	-	-
12. San Juan	13	13	<11	<11	<11	<11	<11	-	-	-	-
13. Garfield	<11	<11	<11	<11	<11	<11	<11	-	-	-	-
14. Columbia	<11	<11	<11	<11	<11	<11	<11	-	-	-	-

Tab. A4. This table reports characteristics of the target WA counties and the dialysis centers that opened in the target WA counties after 2008. Patient volume cells with fewer than 11 patients are displayed as having "<11" patients in accordance with my data use agreement. See the discussion near page 72. Data source(s): Data reported in columns (2)-(7) are from the USRDS. Data reported in columns (8)-(10) are from the Medicare Facility Reports.

	(1) 1[Entries>0]
RD	0.691***
	(0.219)
BW-L	2.0
BW-R	4.5
N	617
Mc-y (t)	-0.56
Mc-y (p)	0.58

SEs clustered at the county-level in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Calonico et al. (2014a)

Tab. A5. This table reports estimates of β from equation 15. See the discussion near page 74. Data source(s): NC dialysis CON program.

	(1) Miles to Chosen Center	(2) 1[Treated In Own County]	(3) Stations Per Patient At Chosen Center	(4) Nurses Per Patient At Chosen Center	(5) Diets. Per Patient At Chosen Center	(6) PCTs Per Patient At Chosen Center
1[Center	-3.1626	0.0412	0.0031	0.0084	0.0010	-0.0017
In County]	(2.8485)	(0.0310)	(0.0090)	(0.0084)	(0.0008)	(0.0066)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	-	-	-	-	-	-
Pat. Char.	-	-	-	-	-	-
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2004, 2015]$	$[2004, 2015]$	$[2004, 2015]$
Window (Yrs.)	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-4, 6]$	$[-4, 6]$	$[-4, 6]$
T. ZCTAs	93	94	94	92	92	92
C. ZCTAs	835	914	913	871	871	871
B-line Y	33.854	0.065	0.272	0.089	0.014	0.096
F-Stat.	15.8	15.6	15.7	15.0	15.0	15.0
N	266,244	298,682	296,896	240,578	240,578	240,578
Clusters	215	219	219	218	218	218
Adj. R^2	0.010	0.060	-0.001	-0.030	-0.018	-0.014

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. A6. This table reports estimates of β from equation (7) for the predicted outcomes discussed in appendix B. Figures A6-A13 plot the event studies associated with these estimates. There is little evidence that significant changes to the patient populations included in the IV-DID analyses explain my IV-DID estimates. See the discussion in section B. Data source(s): USRDS.

	(1)	(2)	(3)	(4)	(5)	(6)
	1[Home HD]	1[Home PD]	1[Any Hosp.]	1[Hosp. For Cardio. Event]	1[Hosp. For Infec.]	1[Death]
1[Center In County]	-0.0099	-0.0307	0.0009	0.0011	-0.0013	-0.0012
	(0.0093)	(0.0198)	(0.0073)	(0.0068)	(0.0037)	(0.0016)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	-	-	-	-	-	-
Pat. Char.	-	-	-	-	-	-
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$	$[2000, 2015]$
Window (Yrs.)	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$	$[-8, 6]$
T. ZCTAs	94	94	87	87	87	94
C. ZCTAs	921	921	882	882	882	921
B-line Y	0.033	0.196	0.106	0.100	0.046	0.012
F-Stat.	14.0	14.0	11.7	11.7	11.7	14.0
N	309,225	309,225	218,142	218,142	218,142	309,225
Clusters	219	219	218	218	218	219
Adj. R^2	-0.004	-0.008	-0.002	-0.002	-0.002	-0.001

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. A7. This table reports estimates of β from equation (7) for the predicted outcomes discussed in appendix B. Figures A6-A13 plot the event studies associated with these estimates. There is little evidence that significant changes to the patient populations included in the IV-DID analyses explain my IV-DID estimates. See the discussion in section B. Data source(s): USRDS.

	(1) Miles to Chosen Center	(2) 1[Treated In Own County]	(3) Stations Per Patient At Chosen Center	(4) Nurses Per Patient At Chosen Center	(5) Diets. Per Patient At Chosen Center	(6) PCTs Per Patient At Chosen Center
1[Center	0.0175	0.0390**	0.0078	-0.0044**	-0.0001	0.0027**
In County]	(0.7717)	(0.0171)	(0.0078)	(0.0019)	(0.0003)	(0.0014)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	-	-	-	-	-	-
Pat. Char.	-	-	-	-	-	-
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	[1993, 2015]	[1993, 2015]	[1993, 2015]	[2005, 2015]	[2005, 2015]	[2005, 2015]
Window (Yrs.)	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$
T. ZCTAs	51	51	51	6	6	6
C. ZCTAs	1,040	1,041	1,040	710	710	710
B-line Y	17.484	0.072	0.269	0.078	0.011	0.081
F-Stat.	74.3	74.9	75.3	293.6	293.6	293.6
N	3,692,043	3,763,287	3,732,737	790,763	790,763	790,763
Clusters	224	224	224	159	159	159
Adj. R^2	-0.001	0.005	0.002	-0.006	-0.001	-0.008

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. A8. This table reports estimates of β from equation (10) for the predicted outcomes discussed in appendix B. Figures A6-A13 plot the event studies associated with these estimates. There is little evidence that significant changes to the patient populations included in the IV-DID analyses explain my IV-DID estimates. See the discussion in section B. Data source(s): USRDS.

	(1)	(2)	(3)	(4)	(5)	(6)
	1[Home HD]	1[Home PD]	1[Any Hosp.]	1[Hosp. For Cardio. Event]	1[Hosp. For Infec.]	1[Death]
1[Center In County]	-0.0047	0.0203**	-0.0011	-0.0023	-0.0012	-0.0007
	(0.0030)	(0.0091)	(0.0037)	(0.0033)	(0.0024)	(0.0006)
Month FE	Y	Y	Y	Y	Y	Y
Region Char.	-	-	-	-	-	-
Pat. Char.	-	-	-	-	-	-
ZCTA FE	Y	Y	Y	Y	Y	Y
Yr. Range	$[1993, 2015]$	$[1993, 2015]$	$[1993, 2015]$	$[1993, 2015]$	$[1993, 2015]$	$[1993, 2015]$
Window (Yrs.)	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$	$[-5, 4]$
T. ZCTAs	51	51	51	51	51	51
C. ZCTAs	1,042	1,042	1,034	1,034	1,034	1,042
B-line Y	0.011	0.116	0.144	0.135	0.061	0.016
F-Stat.	74.1	74.1	64.3	64.3	64.3	74.1
N	3,823,506	3,823,506	3,090,919	3,090,919	3,090,919	3,823,506
Clusters	224	224	224	224	224	224
Adj. R^2	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001

County-level cluster-robust SEs in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Tab. A9. This table reports estimates of β from equation (10) for the predicted outcomes discussed in appendix B. Figures A6-A13 plot the event studies associated with these estimates. There is little evidence that significant changes to the patient populations included in the IV-DID analyses explain my IV-DID estimates. See the discussion in section B. Data source(s): USRDS.

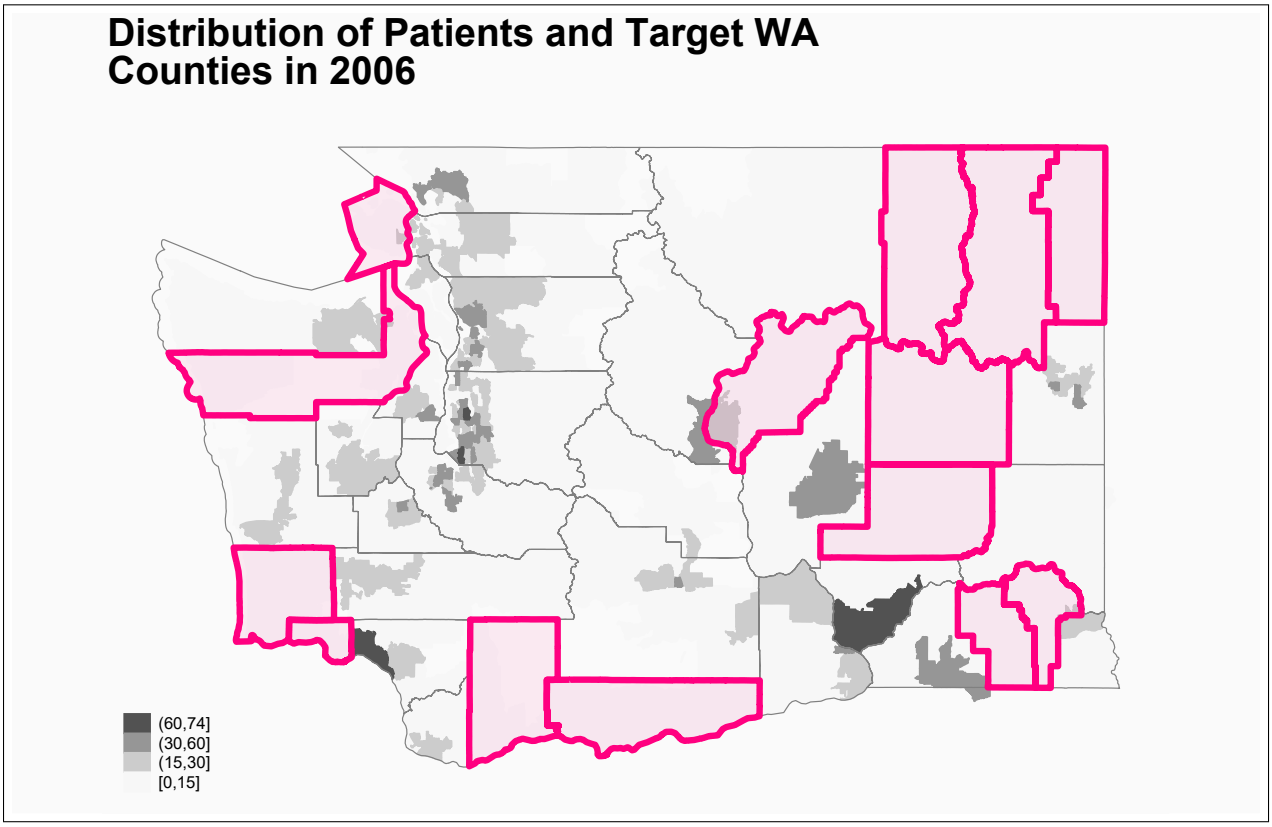


Fig. A1. This figure is a map of Washington. It plots the geographic distribution of the WA dialysis patient population by ZCTA. It also identifies in pink, bold lines the target WA counties. Note that many of the target WA counties border one another. See the discussion near page 17. Data source(s): USRDS.

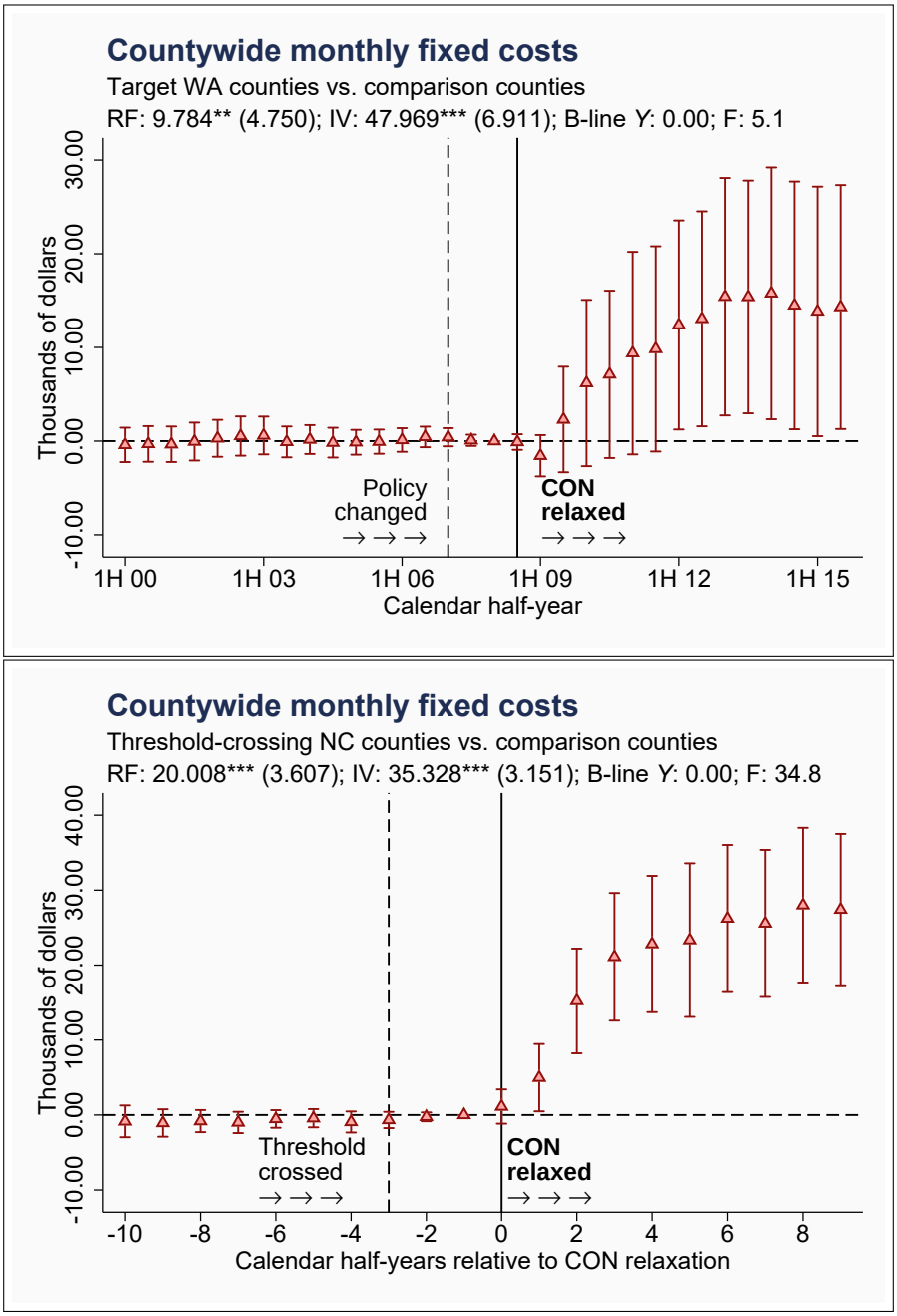


Fig. A2. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equations (8) and (11) and their 95% confidence intervals for the county-level fixed cost outcome described in section III.D. The figure headings report the corresponding estimates from the static analogues of equations (8) and (11), the IV-DID estimates from equations (7) and (10), the baseline average values of the outcome, and the first-stage F-statistics. Data source(s): USRDS and HCRIS.

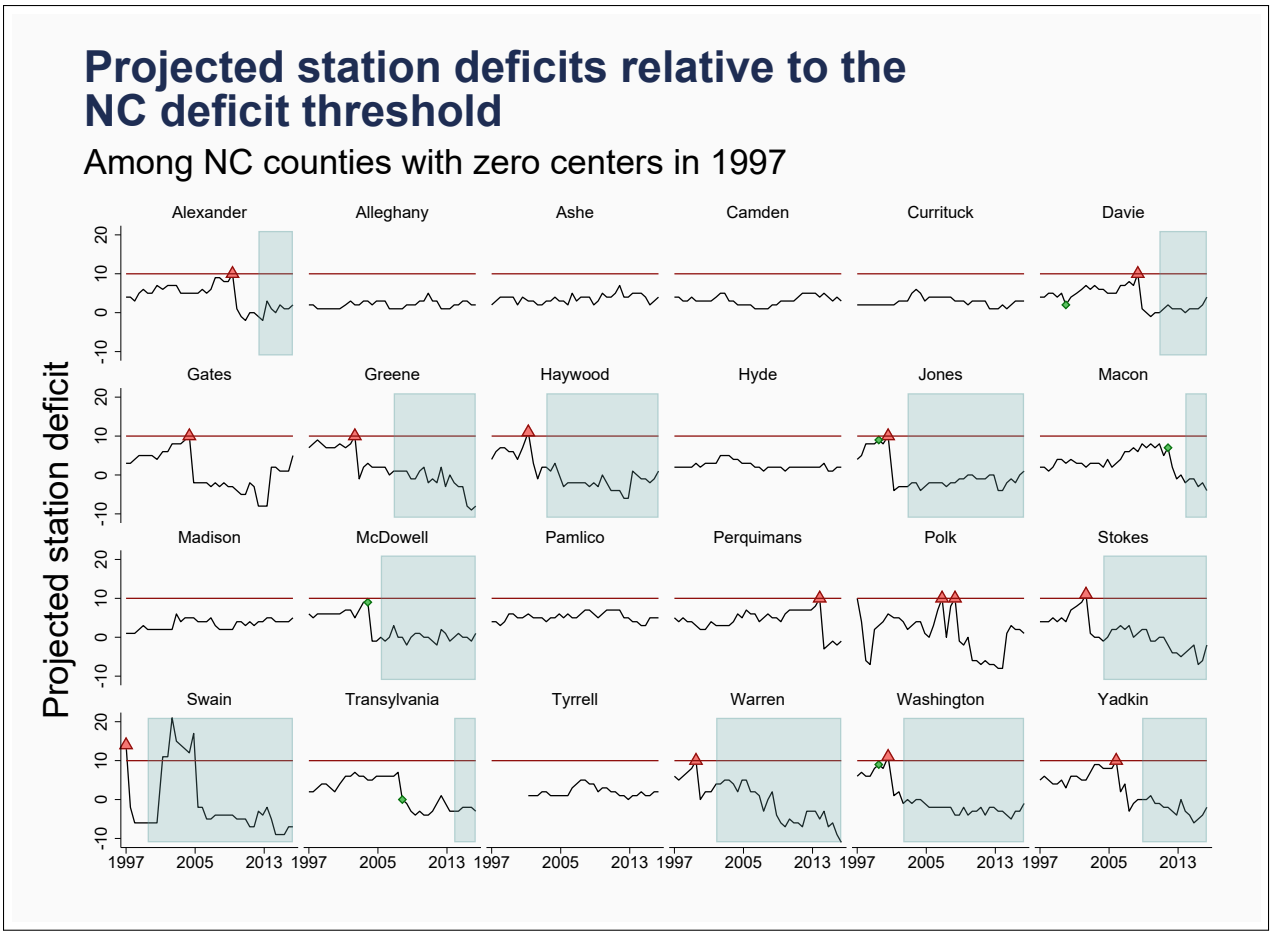


Fig. A3. This figure plots the projected station deficit between 1997 and 2016 for the 24 NC counties that were reported to have had zero dialysis centers in March 1997 by the NC dialysis CON program. The red horizontal line is the NC deficit threshold. Applications filed while the projected station deficit was above the NC deficit threshold are marked by a red triangle. Other applications are marked by a green diamond. Shaded regions are regions where the NC dialysis CON program reported that a dialysis center was operating. This figure shows that when a county's resident in-center patient population crossed the NC deficit threshold in a county without a dialysis center, an application to open a new dialysis center was usually immediately filed and a center usually subsequently opened. See the discussion near page 73. Data source(s): NC dialysis CON program.

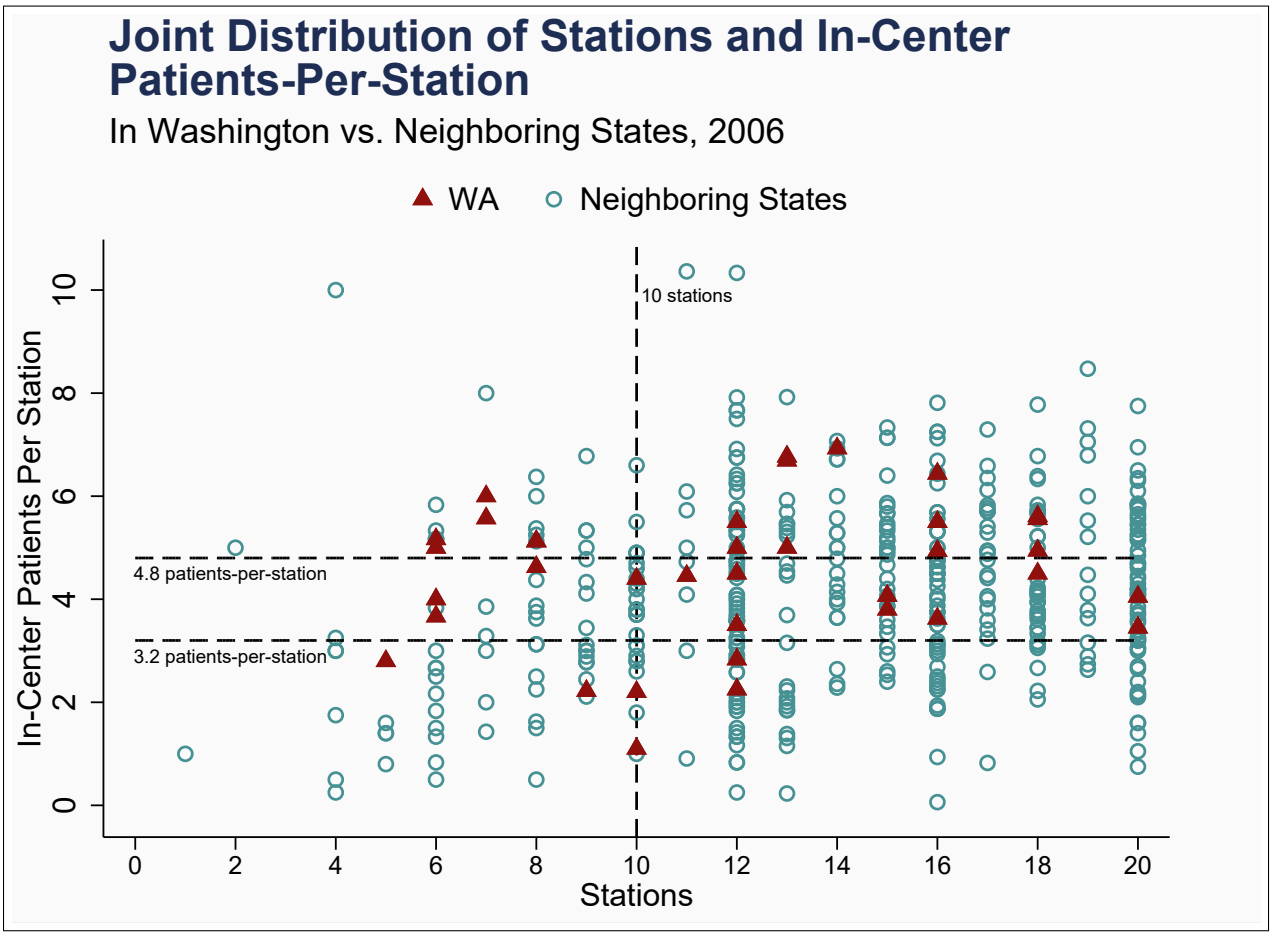


Fig. A4. This figure plots the joint distribution of Washington's dialysis centers' capacities and patients-per-station in 2006. See the discussion near page 72. Data source(s): USRDS.

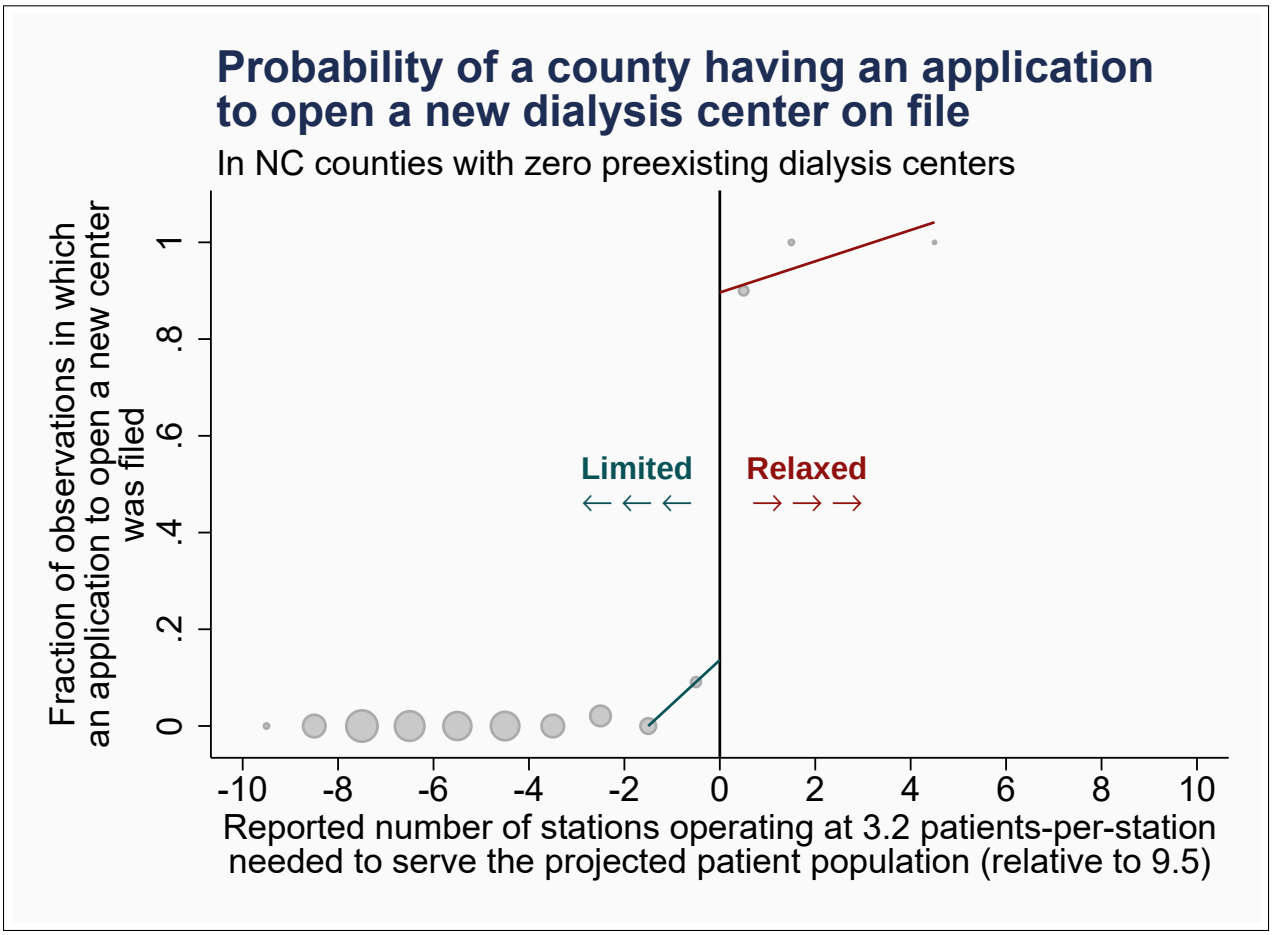


Fig. A5. This figure plots the estimated probability that a NC county without any dialysis centers experienced an application filing by a potential entrant seeking to open a new dialysis center as a function of the county's projected station deficit. It shows that NC counties without any dialysis centers were discontinuously more likely to have experienced an application filing when their projected station deficit was at least 9.5 stations. See the discussion near page 74. Data source(s): NC dialysis CON program.

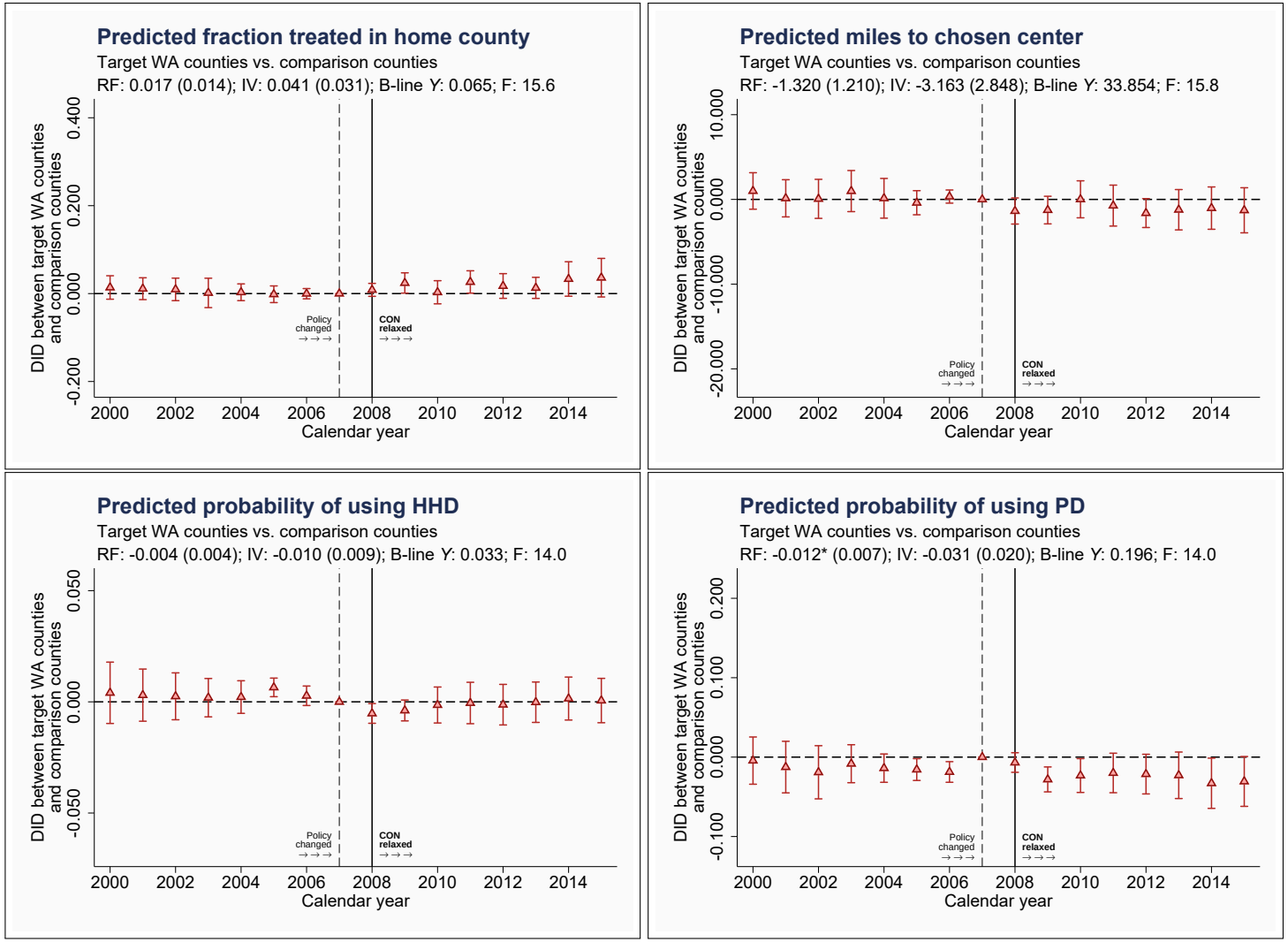


Fig. A6. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

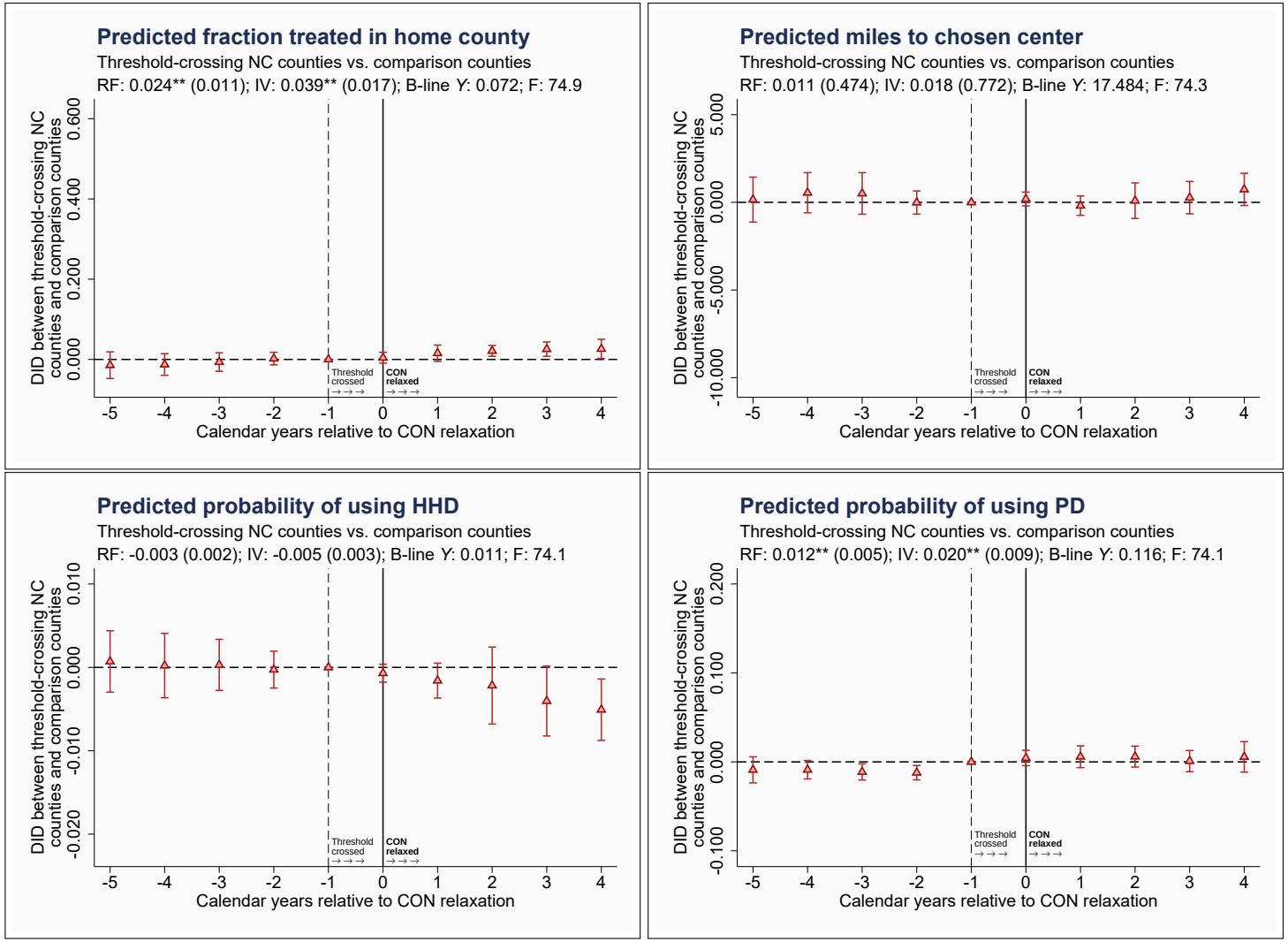


Fig. A7. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

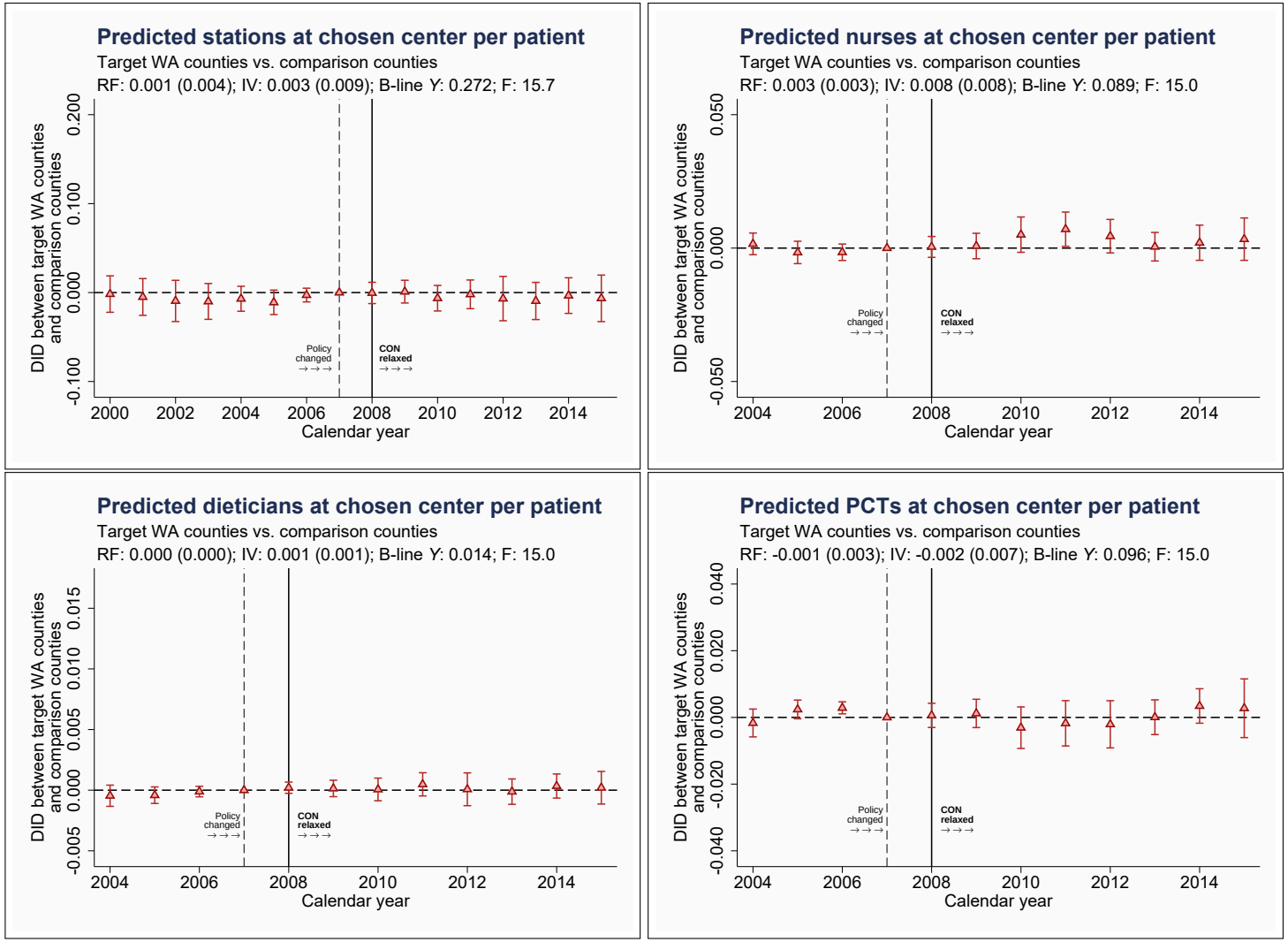


Fig. A8. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

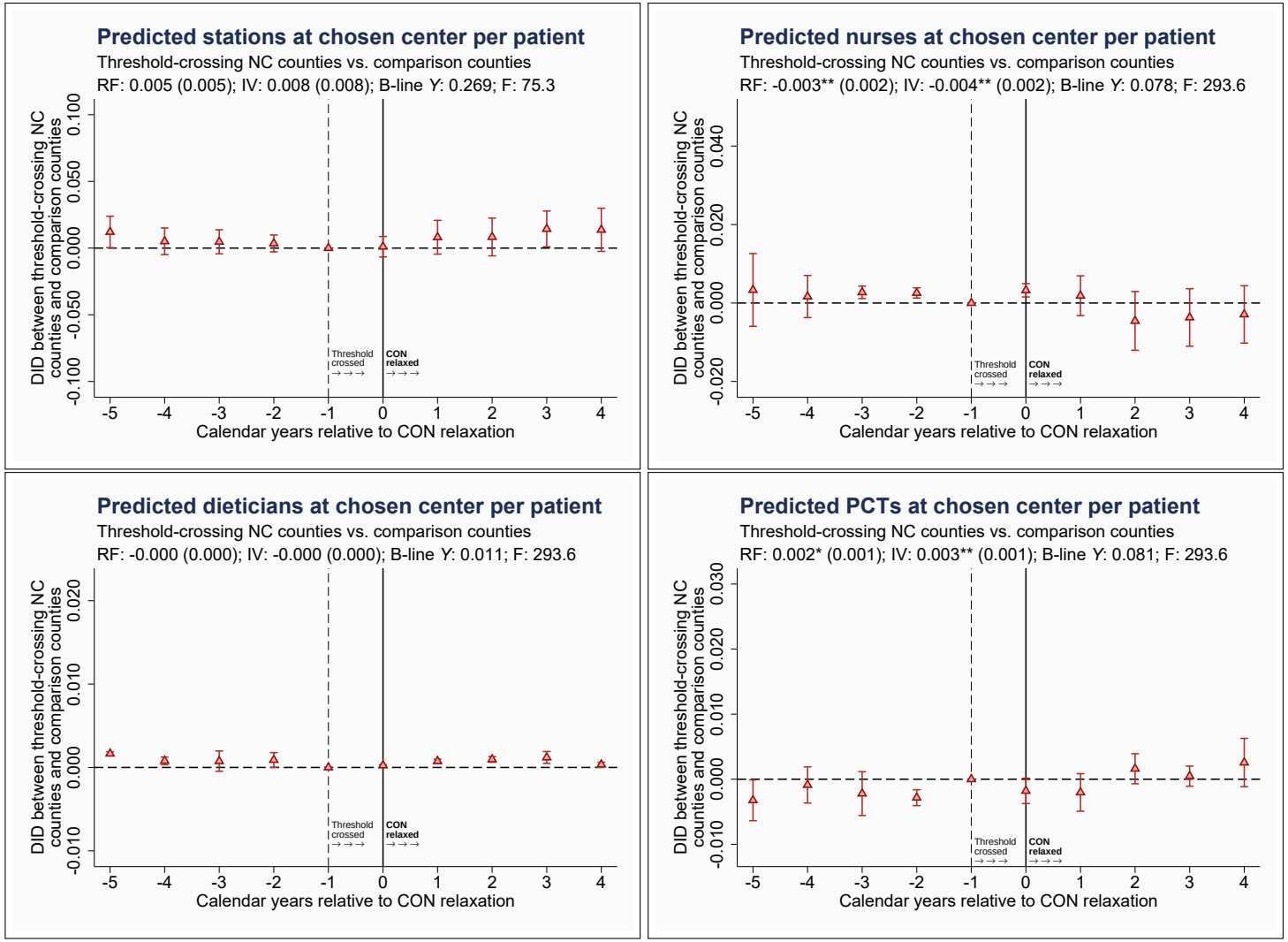


Fig. A9. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

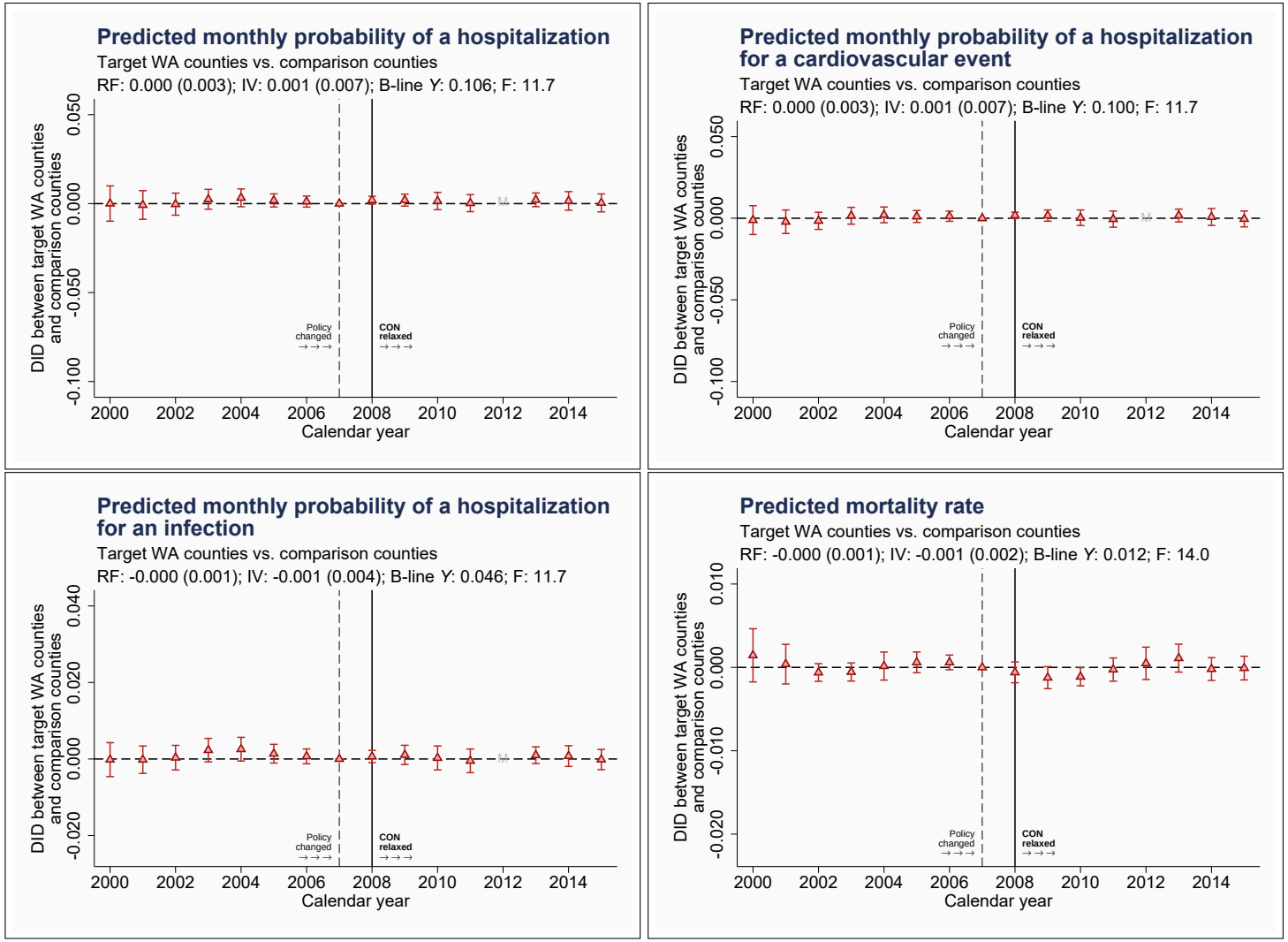


Fig. A10. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

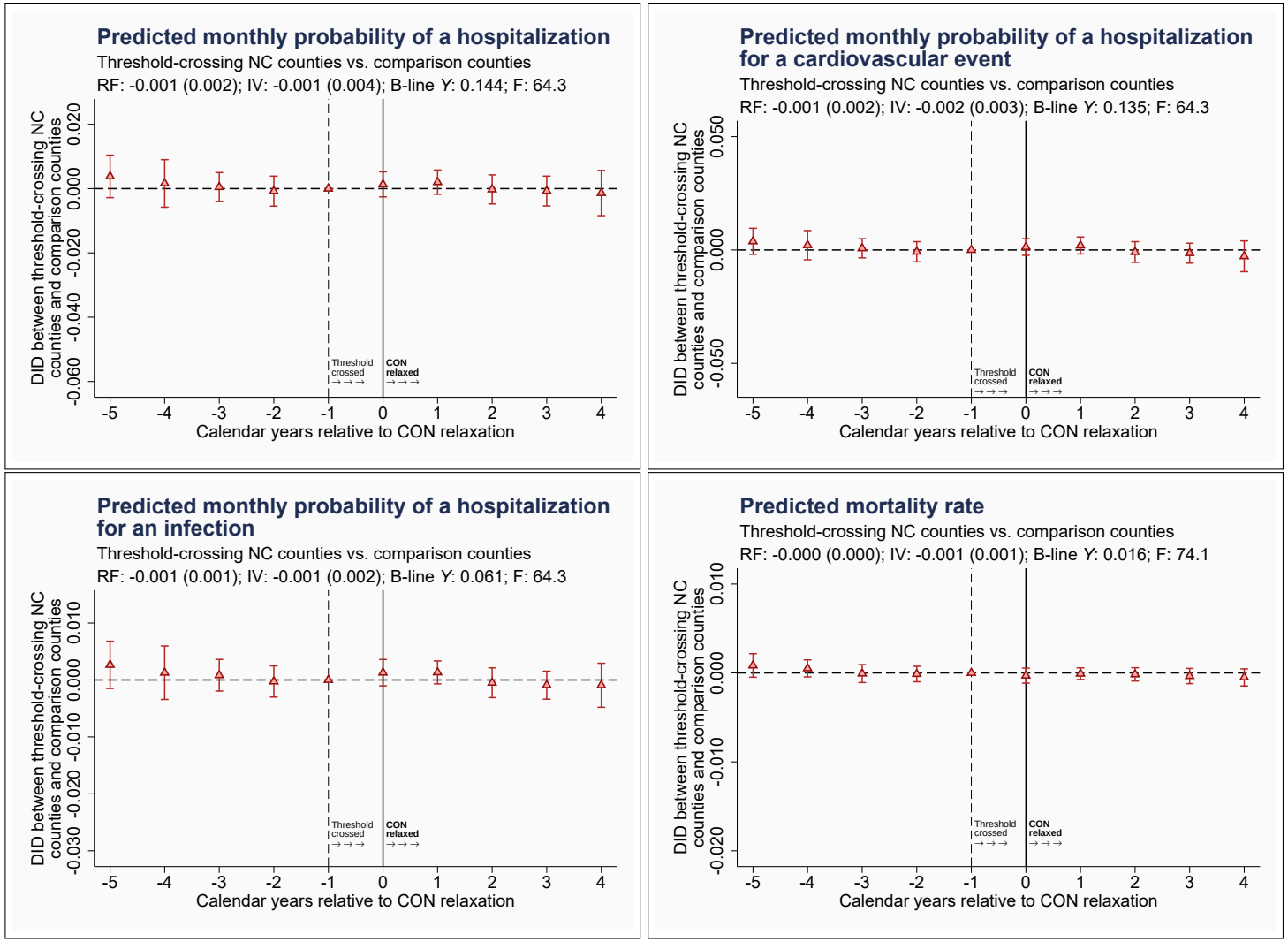


Fig. A11. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

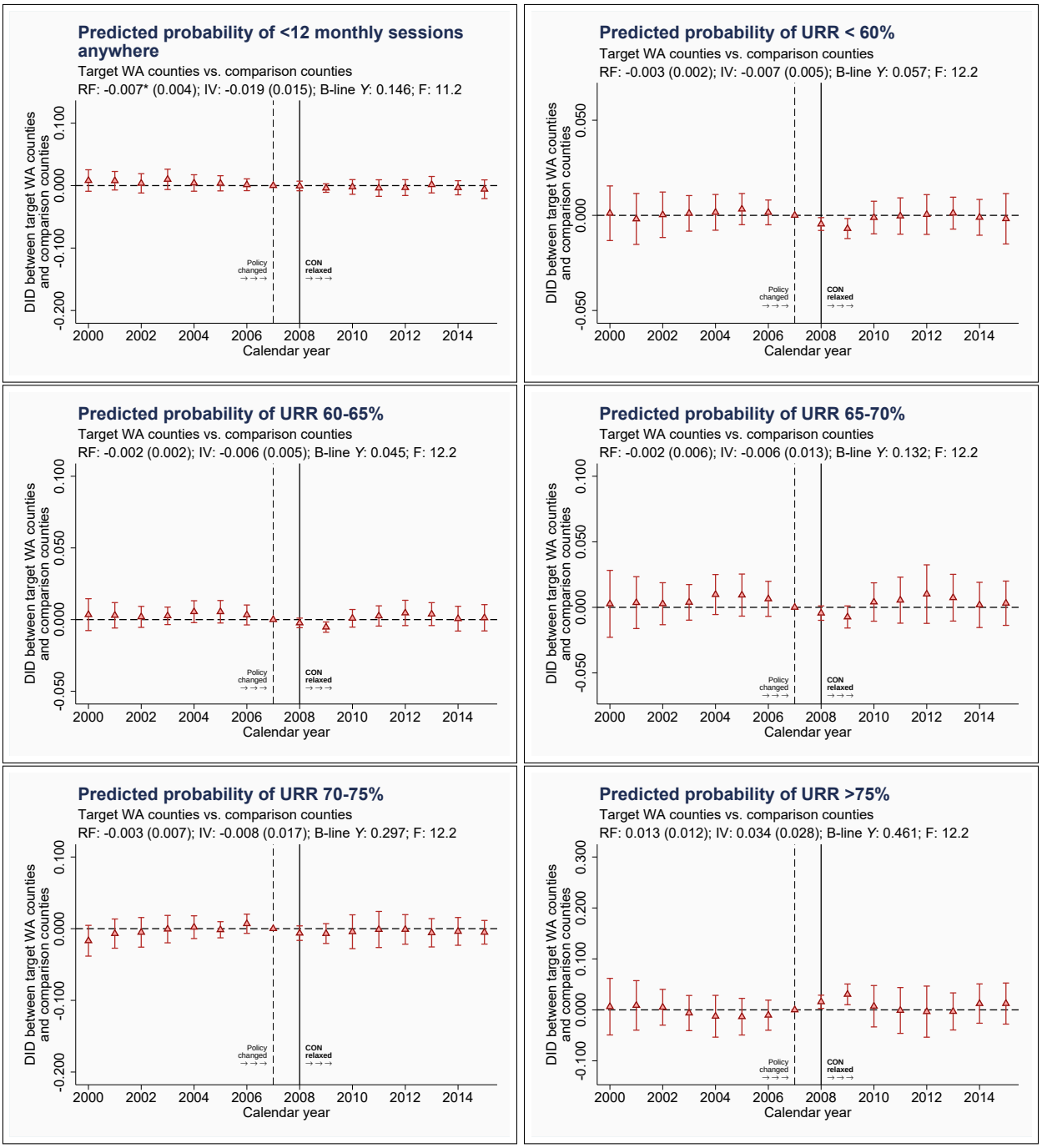


Fig. A12. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (8) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (8), the IV-DID estimates from equation (7), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in appendix B. Data source(s): USRDS.

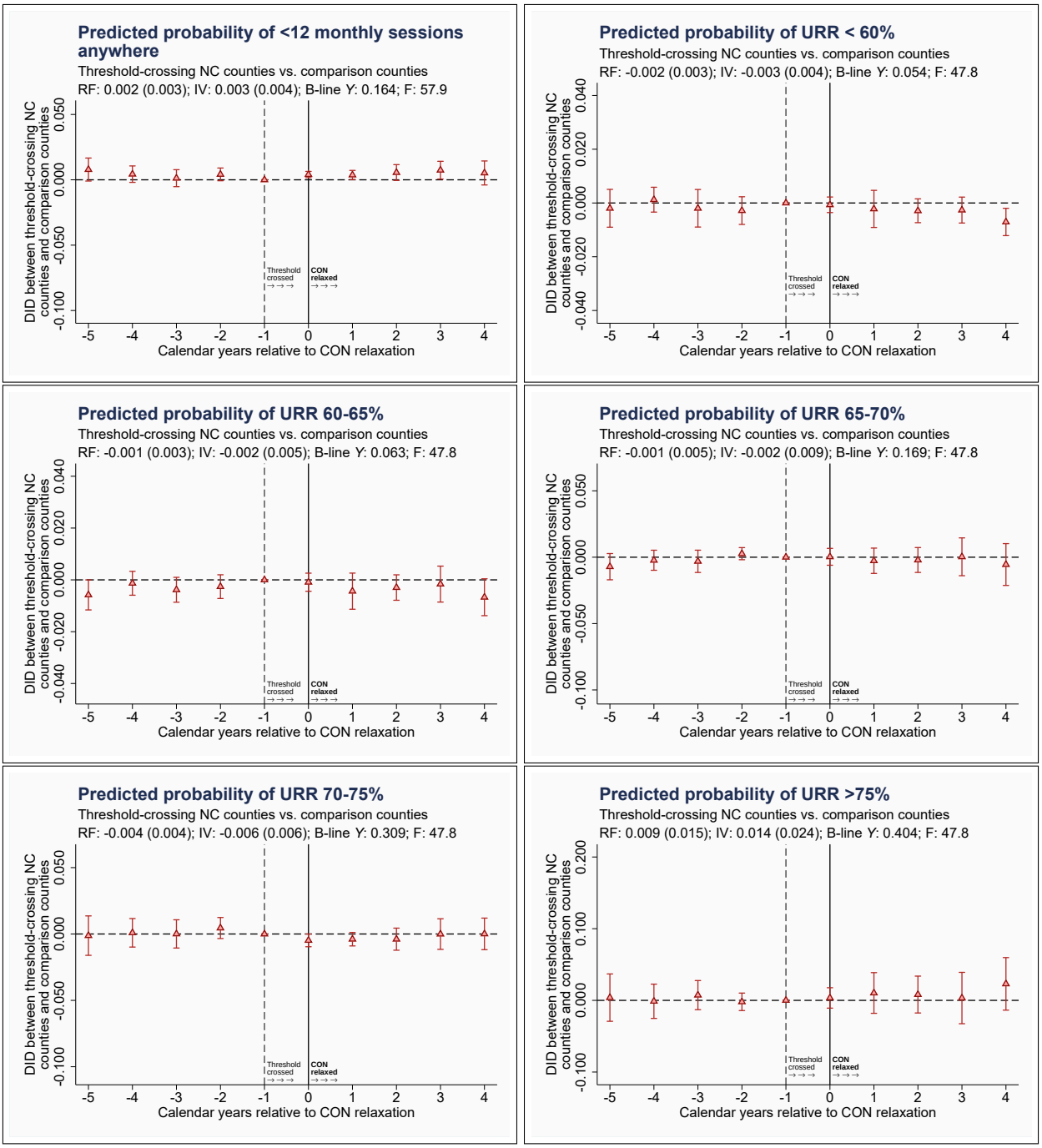


Fig. A13. This figure plots estimates of $(\omega_l : l \in \mathcal{L})$ in equation (11) and their 95% confidence intervals for the predicted outcomes discussed in appendix B. The figure headings report the corresponding estimates from the static analogues of equation (11), the IV-DID estimates from equation (10), the baseline average values of the outcome, and the first-stage F-statistics. The axis scale is the same as the scale used to plot the corresponding estimates for the main outcomes of interest. See the discussion in section B. Data source(s): USRDS.