Safety Net Crowd-Out: How Public Programs Affect Non-Profit Hospital Charity Care

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Abstract

Medical organizations in the US provide billions of dollars of free and discounted healthcare to uninsured and low-income patients each year. This paper examines the interplay between the two largest providers of this safety net healthcare: private hospitals and the public sector. Using federal tax returns from non-profit hospitals and difference-in-differences strategies, I analyze how increases in the public healthcare safety net affect the private provision of charity care. I find that a one standard deviation increase in publicly funded health centers per capita is associated with a 9% decrease in non-profit hospital charity care spending from hospitals in the same county as these centers. Further, state-level Medicaid expansions coincide with a 35% decrease in non-profit hospital charity care. Finally, I show that non-profit hospitals do not change their financial assistance policies following either of these local increases in the public safety net, but rather allow their charity spending to fall with demand. These findings provide substantial evidence of public spending crowding out private charity in the healthcare sector.

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1 Introduction

The United States is unique among OECD nations with a large share of the country's population lacking health insurance coverage, with nearly 30 million uninsured Americans in 2019 (Kaiser Family Foundation, 2020). Despite lacking insurance and often the ability to pay out-of-pocket, these individuals still require healthcare and many medical providers still serve them. In 2017, public and private medical organizations provided over $45 billion of free or discounted care to uninsured patients, commonly known as "uncompensated care" since these services are never formally paid for by patients nor by insurance companies (Karpman, Coughlin, and Garfield, 2021).

Uncompensated healthcare is provided by many different entities, including hospitals, public programs, and non-profit organizations. Hospitals are the largest providers of uncompensated care, regularly contributing nearly $26 billion annually ($20 billion to uninsured patients and another $6 billion to low-income insured patients; Roth, Naber, Metz, and Nikolova, 2021). Non-profit hospitals, in particular, administer a substantial amount of uncompensated care compared to their for-profit counterparts (Tahk, 2014). Publicly funded programs, such as community-based Federally Qualified Health Centers (FQHCs), are the second largest providers of uncompensated healthcare. State and federal governments also contribute to the U.S. healthcare safety net more broadly by offering public health insurance to low-income individuals through state-level Medicaid programs.

This decentralized provision of safety net healthcare raises a crucial question: how does an increase in safety net care provided by one channel affect that provided by another? This paper explores this question by analyzing how increases in the public provision of safety net healthcare affect the provision of charity care at private non-profit hospitals. Specifically, I examine two important parts of the public healthcare safety net: (1) increases in federally subsidized in-kind healthcare through changes in FQHC presence in communities surrounding non-profit hospitals, and (2) public health insurance expansions through state-level Affordable Care Act (ACA) Medicaid expansions.

The relationship between in-kind public and private provisions of safety net healthcare has yet to be thoroughly examined by the economics and public health literatures. FQHCs, like non-profit hospitals, provide a substantial amount of in-kind healthcare to uninsured and low-income individuals. In exchange for federal funding and higher Medicare and Medicaid reimbursement rates, these primary care centers must indiscriminately provide care to all community members and offer fee schedules with income-based discounts. The prevalence of FQHCs has grown dramatically over recent decades. By 2019, they operated over 13,000 locations and served more than 30 million people, including nearly one in five uninsured Americans and one in three individuals living below the poverty line (Health Resources & Services Administration, 2020).

The impact of increasing public provision of in-kind safety net healthcare on non-profit hospital provision is theoretically ambiguous, with two potential channels of influence. First, public contributions via FQHCs could either substitute or complement the demand for hospital charity care. For instance, FQHCs might act as substitutes if preventative care improves overall health or if access to primary care physicians reduces inefficient use of emergency departments. Conversely, they might complement hospital services if access to primary care increases specialty care referrals or encourages patients to seek hospital care, knowing follow-up care is available. Second, non-profit hospitals may respond to changes in charity care demand by either allowing their charity care expenditures to fluctuate with demand or by adjusting their financial assistance policies to maintain constant charity care expenditures. The latter approach might be favored if hospitals aim to consistently provide a designated amount of charity care to justify their tax-exempt status.[1]

To analyze this relationship between FQHCs and non-profit hospital charity care, I use a relatively new source of non-profit hospital financial data: Internal Revenue Service (IRS) Form 990 federal tax returns. The IRS Form 990 data provide a consistent breakdown of hospital uncompensated care into (1) charity care—defined as unreimbursed services for which the hospital neither received—nor expected to receive—any payment—and (2) bad debt—defined as unreimbursed services for which the hospital anticipated—but ultimately did not receive—payment. Further, the data are unique in quantifying both hospital expenditures as well as hospital policies related to charity care. Both of these measures are necessary in order to distinguish between changes in charity care spending that are due to changes in demand from those that are due to deliberate changes in hospital policy.

With this data and a difference-in-differences strategy exploiting geographic and time variation in FQHC presence across communities, I find that a one standard deviation increase in the number of FQHCs per baseline uninsured people in a county is associated with a statistically significant 9% decrease in non-profit hospital charity care spending among hospitals located in the same county. In contrast, I find no significant change in total hospital uncompensated care (i.e., charity care and bad debt) and no significant changes in the income eligibility thresholds in non-profit hospitals' financial assistance policies following increases in FQHC presence.

[1] There is an active policy debate over whether non-profit hospitals provide enough "community benefits," including charity care, to justify their tax-exempt status. See, for example, Senator Grassley's investigations with the Senate Finance Committee discussed in https://www.nytimes.com/2009/06/01/us/politics/01health.html and https://www.modernhealthcare.com/government/grassley-back-it-ramping-up-scrutiny-tax-exempt-hospitals.

These findings are robust to a number of specification checks, and event study estimates reveal no obvious pre-trends in outcomes that would threaten my identification assumption of parallel trends.

Next, I analyze the effect of public health insurance expansions on charity care provision at private non-profit hospitals by examining state-level Affordable Care Act (ACA) Medicaid expansions. A key distinction between public health insurance and public in-kind healthcare is that insurance directly reduces the price of hospital-level care, while in-kind services do not. Consequently, increases in public health insurance may more strongly complement the demand for hospital services than increases in public in-kind healthcare. However, this increased demand would be for insured services rather than for charity care. The previously discussed mechanism of how non-profit hospital behavior may respond to demand changes still applies: non-profit hospitals could either respond to changes in demand by allowing charity expenditures to fluctuate or by adjusting financial assistance policies to maintain constant charity expenditures. Thus, overall, relationship between public health insurance expansions and private non-profit hospital charity care spending remains theoretically ambiguous.

Using the same data and a difference-in-differences strategy around state-level Medicaid expansions, I find that Medicaid expansions result in a sharp 35% reduction in non-profit hospital charity care and a 29% decrease in non-profit hospital total uncompensated care spending. This finding is consistent with the prior literature (e.g., Cunningham, Hadley, Kenney, and Davidoff, 2007; Nikpay, Buchmueller, and Levy, 2015; Dranove, Garthwaite, and Ody, 2016; Sachs, 2019a). I also uniquely find that this reduction persists over multiple years. I also find that Medicaid expansions are not associated with any changes in non-profit hospital financial assistance policies. These results are robust to a number of specification checks including the Callaway and Sant'Anna (2021) estimator.

Together, these findings provide substantial evidence of public spending crowding out private spending on safety net healthcare. Neither public increases in in-kind charity healthcare nor health insurance coverage cause changes in non-profit hospital charity care policies, but both lead to large reductions in non-profit hospital charity care spending.

Related Literature This work contributes to several related literatures. First, this analysis extends our understanding of crowd-out effects in markets with both public and private agents. While previous studies in the crowd-out literature have focused on crowd-out between public and private health insurance (e.g., Cutler and Gruber, 1996; Brown and Finkelstein, 2008; Gruber and Simon, 2008; Frean, Gruber, and Sommers, 2017), between private health insurance and private charity healthcare (Herring, 2005; Lo Sasso and Meyer, 2006), or between private charitable organizations (Hsuan et al., 2019; Sachs, 2019b), my paper uniquely examines the interaction between public and private charity healthcare provision. This fills a crucial gap in understanding how public and private sectors interact in providing essential services.

Second, this paper contributes to the small but growing literature on the determinants of hospital charity care. In addition to the papers examining the effect of Medicaid expansions (Cunningham et al., 2007; Nikpay et al., 2015; Dranove et al., 2016; Sachs, 2019a), this literature has found that hospital uncompensated care spending responds to local demand changes from neighboring hospital closures and increases in the uninsured population (Garthwaite, Gross, and Notowidigdo, 2018) as well as state-level regulations that are enforced by court actions (Sachs, 2019a). I extend this research by examining the long-term effects of Medicaid expansions and introducing the novel factor of public in-kind healthcare provision. My analysis of hospital financial assistance policies also adds depth to the limited existing research in this area.

Third, this analysis enhances the literature on impacts of FQHCs on local communities. While previous studies have demonstrated the positive health effects of the initial roll-out of FQHCs in the 1960s and 1970s (Bailey and Goodman-Bacon, 2015; Kose, O'Keefe, and Rosales-Rueda, 2022) and the more recent effects of FQHCs on Medicaid and Disability Insurance enrollment (Gray, 2019; Anstreicher, 2021), this paper is the first to evaluate the impact of the FQHC program on nearby non-profit hospital charity care. This contributes to a more comprehensive understanding of the role of FQHCs in the broader healthcare system. By examining these intersections, this paper provides valuable insights into the complex dynamics of safety net healthcare provision in the United States.

Outline The remainder of the paper is structured as follows: Section 2 describes my data sources. Section 3 analyzes the effect of FQHCs on private hospital charity care spending and policies. Section 4 investigates the effect of Medicaid expansions on private hospital charity. Section 5 concludes.

2 Data

In this paper, I use two main types of data: (1) data on non-profit hospitals, and (2) data on Federally Qualified Health Centers (FQHCs).

2.1 Hospital Data

I use two separate data sources for non-profit hospitals. First, I utilize annual federal tax returns titled IRS Form 990, focusing particularly on the non-profit hospital specific Schedule H. This schedule requires hospitals to disclose their expenditures on charity care, bad debt, and a variety of other community benefits. Schedule H also requires hospitals to list the criteria in their financial assistance policies (FAPs) from which they determine whether patients are eligible for charity care. These criteria involve income thresholds for free or discounted care that are bench-marked to the federal poverty level (FPL). If a patient has a family income under a certain percentage of the FPL based on her family size (e.g., 150% of the FPL, which is $41,625 for a family of four in 2022), then a hospital's FAP states that the patient is not responsible for any amount of her hospital bill that is not covered by insurance. If a patient has a family income under a slightly higher percentage of the relevant FPL (e.g., 200% of the FPL, which is $55,500 for a family of four in 2022), then the patient is eligible for discounts on any amount of her hospital bill that is not covered by insurance. However, if a patient has a family income over this second benchmark (e.g., 200% of the FPL), then the patient receives no financial assistance. In addition to income requirements, some hospitals have asset requirements for eligibility; unfortunately, though, the IRS 990 data only includes information on income thresholds. Thus, it possible that one of the reasons I do not find effects of public increases in the healthcare safety net on non-profit hospitals' FAPs is that these hospitals are changing their asset requirements rather than their income thresholds. I cannot rule out this explanation.

I obtain these tax returns from digital records hosted on Amazon Simple Storage Service and printed records transcribed by GuideStar. My final sample contains returns from 2010 to 2018.[2] Another limitation with this data is that the information included in the returns is at the organization level rather than at the individual hospital level. Approximately 15% of organization filers operate multiple hospital facilities (e.g., Kaiser Permanente, Dignity Health, etc.), and approximately 35% of non-profit hospitals are operated by these organizations. Since total charity care levels and policies at the organization level may not be reflective of individual hospitals, I limit my sample to only include hospitals owned by organizations that operate a single hospital facility.

[2] Electronically-filed IRS 990 forms are publicly available via Amazon Simple Storage Service beginning in 2015. While some non-profit hospitals' IRS 990 forms are publicly available for earlier years through sources such as ProPublica's Nonprofit Explorer, these pre-2015 records are not in an easy-to-compile format. Thus, I obtained data for 2010-2014 from GuideStar, an organization that collects, digitizes, and sells information on the entire population of U.S. tax-exempt organizations' Form 990 tax returns. While some hospitals have filed Form 990 tax returns for 2019, they represent a small fraction of the non-profit hospital population. I thus limit my data sample to 2010-2018.

Second, I use the American Hospital Association (AHA) annual surveys for information on hospital characteristics. I match this AHA annual survey data to the IRS records using facility names and addresses. I then further restrict my sample to include only hospitals classified as community hospitals and acute care hospitals (which represent 89% of my remaining IRS records). As a result, my final sample includes 2,054 unique hospital filers and an average of 1,616 hospital records per year.

Table 1 presents summary statistics from the AHA (Panel A) and IRS (Panel B) data. My analysis focuses primarily on five hospital outcomes in the tax returns: (1) the percentage of hospital expenditures attributed to charity care, (2) the percentage of hospital expenditures attributed to either charity care or bad debt (i.e., uncompensated care), (3) the percentage of hospital expenditures spent on all community benefit programs and activities (which includes the amount spent on charity care but not that spent on bad debt), (4) the FPL threshold under which patients are eligible for free care at a given hospital (i.e., the free care threshold), and (5) the FPL threshold under which patients are eligible for discounted care at a given hospital (i.e., the discounted care threshold). Table 1 shows that the average non-profit hospital spent 1.95% of total expenditures on charity care, 6.55% on uncompensated care, and 7.99% on total community benefits. Further, 97% of hospitals in my sample had a free care policy that utilized a FPL family income threshold, while 89% had a discounted care policy that utilized a FPL family income threshold. Among those with such policies, the average threshold to qualify for free care was a family income of less than 182% of the FPL, while the average threshold to qualify for discounted care was a family income of less than 330% of the FPL.

Table A1 compares these summary statistics to those from the full population of non-profit hospitals in the AHA and IRS data. The non-profit hospitals analyzed in this paper are on average smaller than those in the population, with fewer beds and annual visits as well as lower levels of annual expenses and revenues. However, the sample used in this paper is quite similar to the population in terms of the five charity outcomes mentioned above. Though the means of these outcomes for the sample and the population are statistically significantly different, these differences are quite small in magnitude.

Figure 1 illustrates the distribution of charity care policies across non-profit hospitals, depicting histograms of free (Panel A) and discounted (Panel B) care policies in 2010. These panels show that income cutoffs for charity care tend to cluster around 100, 200, and 300% of the FPL. Discounted care income thresholds are more dispersed than free care thresholds. Appendix Figure A1, Figure A2, and Figure A3 delve more into the differences in hospital charity care policies across different communities. Figure A1 and Figure A2 highlight that Northeastern states, as well as Florida and California, tend to have the most generous charity care policies, while Southern and Western states on average spend larger shares of their annual expenditures on charity care and uncompensated care.

Figure A3 shows that hospitals in wealthier areas have higher charity care thresholds and provide more charity care than those in poorer areas, but also that they spend significantly less on bad debt and total community benefits. Since hospital services tend to be local, these correlations likely reflect the fact that hospitals in poorer communities face the largest demand for charity care and fewer financial resources.[3]

Table 2 highlights that hospitals do change their charity policies over time, with 44% of all hospitals changing their free care thresholds and almost half changing their discounted care thresholds at least once between 2010 and 2018. The majority of these changes involved threshold increases, meaning that the policies became more generous over time, with an average increase in the free care threshold of almost 75 percentage points of the FPL and an average increase in the discounted care threshold of 120 percentage points of the FPL. However, more than 30% of the policy changes were decreases, meaning that the policies became less generous. Further, Panels C and D of Figure 1 show that the average non-profit hospital that changes its free or discounted care thresholds during my sample window does so only once.

The fact that non-profit hospitals do change their FAPs suggests that it may be important to examine both charity expenditures and policies when analyzing the effect of changes in the public healthcare safety net on non-profit hospital charity. However, simultaneously, Figure 2 indicates that these charity policies may not have any actual impact on hospital behavior. Figure 2 plots changes in hospital FAP income eligibility thresholds on the x-axis against changes in charity expenditures on the y-axis, cycling through the two main policy measures (i.e., free care and discounted care thresholds) and the three main expenditure measures (i.e., charity care, uncompensated care, and total community benefits). Across all six panels, the estimated slope is almost always zero and insignificant, implying a zero correlation between policy changes and spending changes. While the slope in Panel C is statistically significant, the magnitude of this slope is tiny relative to the mean of hospital uncompensated care. Overall, these panels are quite striking. They show that large changes in hospital FAPs do not translate into any economically significant changes in hospital charity spending. This result suggests that these FAPs might not contain useful information regarding hospital behavior. However, these figures could also be consistent with hospitals responding to anticipated changes in demand by ad-

[3] I am not the first to discover this relationship between local median household incomes and charity care; in fact, Dranove, Garthwaite, and Ody (2015) use the finding that patients who would qualify for charity care at a hospital in a wealthier community would not be eligible for charity care at a hospital in a poorer community as the basis for their "floor-and-trade" policy recommendation.

justing their FAPs to offset anticipated spending changes, i.e., to keep their amounts of charity spending constant over time.

2.2 FQHC Data

I also use two separate data sources for FQHCs: (1) the Uniform Data Set (UDS) collected by the U.S. Health Resources & Services Administration (HRSA), and (2) the Provider of Service (POS) file collected by the U.S. Center for Medicare & Medicaid Services (CMS). The UDS contains information from the annual forms that all FQHCs receiving funding from the HRSA must complete in order to continue receiving funding. The latest six years of these reports are publicly available on the HRSA website; I received the earlier years via a Freedom of Information Act request.[4] This data provides exact addresses for FQHC sites as well as information on funding, patients, employees, and services. To offset some volatility in the UDS, I supplement the UDS with publicly available POS files.[5] Adding the POS data to the UDS data increases the number of FQHC site-year observations in my sample by approximately 15%. My main results are robust to excluding these POS additions (see Appendix Figure A5).

I combine these data sources to quantify and locate active FQHC sites in the U.S.[6] Note that going forward, I use the terms "FQHC" and "clinic" interchangeably to refer to individual service sites rather than entire organizations. Figure 3 depicts the number of active clinics across the U.S. from 1996 to 2018. Over these 22 years, the number of clinics has nearly quadrupled. This rise has been particularly pronounced over years for which I have data on non-profit hospitals, with the number of clinics growing from 8,990 in 2010 (highlighted with the dashed vertical line) to 14,574 in 2018. Appendix Figure A4 maps the locations of active clinics in 2010 (Panel A) and 2018 (Panel B), showing the geographic distribution.

Appendix Table A2 provides some basic summary statistics for FQHC organizations, highlighting the average number of clinics, number of patients, and magnitude and composition

[4]Colin Gray received the earlier years via a FOIA request and generously shared the data with me.

[5]There is imperfect overlap between the two sources in each year. A clinic may be listed in the UDS but not the POS files for a variety of reasons, such as: they may not accept Medicare, they may share a CMS provider identifier with a related site, or they may be part of a larger organization with its own non-FQHC certification (e.g., a hospital or a rural health network). A clinic may be listed in the POS files but not in the UDS if they are not actively receiving HRSA funding even if they are still classified as a FQHC.

[6]I clean, parse, and geocode the recorded addresses using three separate geocoding APIs (Open Street Map API, Census API, and Google Maps API). This allows me to pinpoint the exact geographic coordinates for over 99% of clinics in the sample. I then remove duplicates (which stem from combining the two data sources as well as errors in the UDS) by rounding these geocoded coordinates to the nearest 0.0005 degrees in latitude and longitude and equating clinics whose coordinates lie within the same 0.0005 degree by 0.0005 degree grid. The precise size of this grid differs slightly based on latitude and longitude. For example, the grid is approximately 56-by-42 meters in Boston but 56-by-50 meters in Miami.

of grant funding for each organization. Unfortunately, this information is only available at the organization level, rather than at the individual clinic level. The average FQHC organization operates 7.6 clinics. Unfortunately, I am not able to distinguish between clinics of different sizes in my analyses nor to exploit variation in clinic sizes and funding levels. This data limitation will likely attenuate my estimates since clinics can be quite heterogeneous.

2.3 Additional Data Sources

In addition to the above sources on non-profit hospitals and FQHCs, I also use data on county-level populations, number of uninsured, and unemployment rates from the U.S. Census Small Area Income and Poverty Estimates (SAIPE), the U.S. Census Small Area Health Insurance Estimates (SAHIE), and the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS), respectively. I also use data on state Medicaid expansions from the Kaiser Family Foundation (KFF). Finally, while most of my clinic analyses are run using variation in clinics at the county level, for robustness I check results when aggregating the number of clinics to the Hospital Service Area (HSA) and to the Commuting Zone (CZ) level. HSAs are groups of zip codes in which more Medicare patients receive hospital care from the hospitals in that area than in any other HSA. HSAs are thus fairly localized hospital markets with typically only one hospital located in each, and there are 3,436 HSAs across the U.S. Following the example of Garthwaite et al. (2018)—who argue that uninsured patients may travel outside of their counties to receive hospital treatments and may seek care based on factors different from Medicare patients, on whom the definition of HSA is based—I also map healthcare sites to the 741 U.S. CZs, which are defined as collections of counties that have strong commuting ties to each other and weak ties to other areas (Tolbert and Sizer, 1996; Autor and Dorn, 2013).

3 Evidence from FQHCs

3.1 Empirical Strategy

A challenge in analyzing the effects of FQHCs on nearby non-profit hospitals is that FQHCs are not randomly assigned to counties. In fact, these clinics are required to locate in geographic areas with few other primary care providers. Studies that use only cross-sectional variation in the number of clinics will thus suffer from potentially severe endogeneity concerns. To alleviate some of these concerns, I utilize the panel nature of my data on non-profit hospitals to estimate a two-way fixed effects model. My main specification is given by:

$$Y_{ht} = \mu_h + \mu_t + \beta Clinics_{ct} + X_{ct} + \epsilon_{ht}, \tag{3.1}$$

where Y_{ht} denotes the hospital outcome for hospital h in county c and year t. As previously discussed, I consider five different measures of hospital charity: (1) the amount of charity care (% of hospital expenditures), (2) the amount of charity care plus bad debt (i.e., uncompensated care; % of hospital expenditures), (3) the amount of total community benefits (% of hospital expenditures), (4) the free care threshold (% of FPL), and (5) the discounted care threshold (% of FPL). μ_h represents a vector of hospital fixed effects, which capture time-invariant differences in observable and unobservable traits across hospitals and thus alleviate some of the endogeneity concerns regarding clinic location choices. μ_t represents year fixed effects, which capture time trends such as those related to US policy and aggregate national shifts in non-profit hospital charity. To address the potential endogeneity concern that clinics prefer to open in counties with growing populations or better (or worse) trending local economies, X_{ct} denotes controls for county-level population and unemployment rates. All standard errors are clustered at the county level. The primary coefficient of interest is β, the coefficient on $Clinics_{ct}$, which is the number of FQHC clinics per 10,000 baseline uninsured residents in county c and year t. The number of clinics is scaled by baseline uninsured to better capture the amount of clinic resources available to individuals living in county c and year t.

The underlying assumption needed to interpret the above regression as identifying a casual relationship is that there are no time-varying county-specific factors correlated with the timing of changes in clinic presence other than those two already included as covariates. To provide support for this assumption, I follow Schmidheiny and Siegloch (2020) and estimate the following "distributed lag" model:[7]

$$Y_{ht} = \mu_h + \mu_t + \sum_{r=-3}^{3} \gamma_r Clinics_{c,t-r} + X_{ct} + \epsilon_{ht}. \tag{3.2}$$

Here, the γ_r's measure the relationship between the number of FQHC clinics per 10,000 baseline uninsured residents and the *change* in the hospital outcome of interest. Thus, the γ_r's are the *incremental* effects of a one unit increase in $Clinics_{ct}$ on hospital outcomes rather than the *cumulative* effects (the latter of which are estimated in the more well-known event study

[7]The distributed lag model allows for a continuous treatment variable, thereby making it more comparable to my baseline model than an event study model that imposes a binary treatment variable (such as the first clinic entry in a county; this type of analysis may be insightful but it is fundamentally different from that analyzed in Equation 3.1).

framework). Note that the pre-treatment incremental effects are denoted by the leads ($r < 0$), and the post-treatment incremental effects are denoted by the lags ($r \geq 0$).

To convert these incremental treatment effects into the more standard cumulative effects, Schmidheiny and Siegloch (2020) show that one must choose a reference period and then sum the distributed lag coefficients moving away from this reference period. I let β_r's denote the cumulative event study coefficients, and I set period $r = -1$ as the reference period such that $\beta_{-1} = 0$. For periods $r < -1$, I cumulate negatively: $\beta_{-2} = -\gamma_{-1}$, $\beta_{-3} = -\gamma_{-1} - \gamma_{-2}$, etc. For periods $r > -1$, I cumulate positively: $\beta_0 = \gamma_0$, $\beta_0 = \gamma_0 + \gamma_1$, etc. The point estimates β_r for $r < 0$ describe the evolution of hospital outcomes for eventually treated hospitals before a change in local clinic presence net of changes in untreated hospitals' outcomes. These estimates allow for a visual evaluation of the parallel trends assumption needed for casual identification in the difference-in-differences specification; if the assumption holds, then the estimates of β_r where $r < 0$ should be close to zero and statistically insignificant. The point estimates β_r for $r > 0$ describe the divergence in hospital outcomes after local clinic presence changes net of changes in control hospitals. These are the average treatment effects of a one unit increase in clinic presence on hospital outcomes relative to the year before said increase.

3.2 Results

Table 3 shows the results of the static two-way fixed effects specification, with each cell representing the estimate of $\hat{\beta}$ from a separate regression. Panel A presents results as discussed above, while Panel B presents results from a specification that regresses the log of the relevant outcome variable on the log of the number of clinics. The first takeaway from this table is that, conditional on the controls discussed above, clinic presence is significantly negatively correlated with non-profit hospital charity care expenditures (Column 1) but not correlated with uncompensated care expenditures (Column 2) nor total community benefits (Column 3). The coefficient in Panel A Column 1 tells us that increasing the number of clinics per 10,000 baseline uninsured residents in a county by one is associated with a 0.02 percentage point decrease in the charity care spending (as a percentage of total hospital expenditures) of that county's non-profit hospital(s). Since hospital charity care has a mean of 1.95%, this 0.02 percentage point decrease represents about a 1% decrease in charity care. Further, note that the mean number of clinics per 10,000 baseline uninsured across the sample is 4.8 with a standard deviation of 8.3. Thus, a one standard deviation increase in the number of clinics per baseline uninsured is associated with a 9% decrease in non-profit hospital charity care.

In contrast, the estimated coefficients in Column 2 are much smaller in magnitude and statistically insignificant, indicating no significant relationship between FQHC presence and hospital uncompensated care. The negative relationship between clinic presence and charity care but not with uncompensated care is interesting, suggesting that non-profit hospitals shift charity care into writing off additional bad debt.

The second takeaway is that the amount of FQHC presence near non-profit hospitals does not appear to affect non-profit hospitals' financial assistance policies (Columns 4 and 5). Coefficients in both Panel A and Panel B are economically small and statistically insignificant.

These findings are robust to slight changes in the regression specification, which are presented in Appendix Figure A5. Scaling the number of clinics by county-level population instead of county-level baseline uninsured produces nearly identical results. Swapping out the year fixed effects with either Census region-by-year fixed effects or Census division-by-year fixed effects—to address concerns that some events (e.g., the ACA or the opioid crisis) may have heterogeneous effects across different parts of the country and may also affect both hospital charity and the number of FQHCs—also yields similar point estimates and confidence intervals. Measuring clinic presence at the CZ level rather than the county level produces coefficients of similar magnitudes but slightly larger standard errors. Finally, excluding the POS data from the analysis and thus relying only on the UDS for clinic information also yields very similar point estimates and confidence intervals. Overall, the relationship between clinic presence and non-profit hospital charity care spending remains negative and statistically significant (at least at the 90% level).

I next test for heterogeneity in these estimates by hospital characteristics, narrowing my focus on the outcomes of charity care and uncompensated care levels (i.e., Columns 1 and 2 of Table 3) in order to reduce the number of regressions that I run. Appendix Table A3 interacts the number of clinics per baseline uninsured with a variety of hospital characteristics, including: whether the hospital is a teaching institution (Panel A), is either owned or affiliated with a church (Panel B), is the sole hospital in their local community (Panel C), is located in a county with above median shares of low-income individuals at baseline (Panel D), has an emergency department (Panel E), or operates its own indigent care clinic (Panel F). The only significant source of heterogeneity I find is that the overall negative correlation between clinics per baseline uninsured and charity care expenditures is driven by hospitals located in counties with above median poverty rates at baseline.

Finally, to probe the validity of the parallel trends assumption, Figure 4 plots the cumulative dynamic effects of county-level clinic presence on hospital outcomes following the previously described transformation of estimates from Equation 3.2. In all panels, the $\hat{\beta}_r$'s in the pre-periods are statistically indistinguishable from zero, consistent with the parallel trends assumption. Although the post-period coefficients lack precision—due to the more demanding dynamic specification—the negative correlation between clinic presence and non-profit hospital charity care expenditures holds across all post periods (Panel A).

4 Evidence from Medicaid Expansions

4.1 Empirical Strategy

Next, I look at the effect of public health insurance expansions on the provision of charity care at private non-profit hospitals by analyzing state-level ACA Medicaid expansions. In 2014, 27 states expanded their Medicaid programs to cover adults under 138% of the FPL. Five additional states followed suit from 2015 to 2018. As mentioned in the introduction, previous studies have found that state-level Medicaid expansions coincide with a sharp reduction in non-profit hospital charity care spending. Despite this large reduction in hospital expenditures on free and discounted care, Sachs (2019a) shows that these Medicaid expansions did not immediately lead non-profit hospitals to change their FAPs in the two years following expansions. I replicate this analysis using additional years of data in order to test whether these spending reductions persist over time and whether the lack of changes in hospitals' FAPs reflects inertia rather than a long-run result.[8] I also check whether these previous findings are robust to more recent econometric critiques of event study models with staggered adoption.

For this analysis, I implement the following event study specification:

$$Y_{ht} = \left(\sum_{r=-6}^{4} \beta_r 1_{\{t=e_h+r\}} \right) + \mu_h + \mu_t + X_{ct} + \epsilon_{ht}. \tag{4.1}$$

Here, r is here defined as the relative year since the state in which hospital h is located expanded Medicaid under the ACA. The event study limits $r \in [-6, 4]$ due to the timing of the expansions and my sample period. Observations outside of this window are captured by indicators, $1_{\{t \leq e_h - 6\}}$ and $1_{\{t \leq e_h + 4\}}$, to represent any lingering lead or lag effects. Once again $r = -1$ is excluded. Standard errors are now clustered at the state level. All other parameters are identical to those in Equation 3.1 and Equation 3.2.

[8]This is plausible under a scenario in which hospitals waited to see how much their annual charity care expenditures would change as the result of decreases in the number of local uninsured before revising their FAPs. It is also plausible under a scenario in which revisions to hospital FAPs take time due internal organizational processes.

4.2 Results

Figure 5 presents the results of this event study, while the results of a static difference-in-difference version without leads and lags are shown in Appendix Table A4. Consistent with the literature, I find that Medicaid expansion coincides with a sharp reduction in non-profit hospitals' charity care and uncompensated care spending, on the order of approximately 1 and 2 percentage points, respectively (Panels A and B). Further, I find that this reduction persists over multiple years following these expansions. Given the means for these variables, these reductions translate to a 35% decrease in charity care spending and a 29% decrease in uncompensated care spending in Medicaid expansion states following the expansion relative to non-expansion states. The lack of significant pre-trends supports the parallel trends identification assumption for this analysis. I find no significant correlation between Medicaid expansion and the total community benefits provided by non-profit hospitals (Panel C), though as previously noted this outcome includes a number of different categories of hospital spending and thus is difficult to interpret. Further, Panels D and E indicate that Medicaid expansions did not incentivize hospitals to change their free or discounted care thresholds even several years after the policy change. This result confirms that the lack of an immediate effect of Medicaid expansions on FAPs was not due to a delay in policy revisions.

Recent econometrics literature has highlighted how event study models that exploit staggered adoptions can lead to biased estimates when the treatment effects are heterogeneous across relative time or units. Since Medicaid expansions were adopted by different states in different years, I test whether negative weighting from treatment effect heterogeneity is biasing my estimates by implementing the estimator proposed by Callaway and Sant'Anna (2021). This approach only uses never-treated and not-yet-treated states as controls for the treated states, thereby avoiding the bias that can result when one uses earlier-treated states as controls for later-treated states. The results of this robustness check are presented in Figure A6.[9]

The Callaway and Sant'Anna (2021) estimates follow the same general patterns as the standard event study estimates for the hospital charity care and uncompensated care spending outcomes (Panels A and B), though the Callaway and Sant'Anna (2021) estimates are slightly larger in magnitude. However, unlike the standard event study estimator, the Callaway and Sant'Anna (2021) estimator finds the hospital spending on total community benefits drops sharply following Medicaid expansions (Panel C). As noted previously, this outcome includes a number of different categories of hospital spending and is difficult to interpret. The Callaway and Sant'Anna (2021) estimator also finds an immediate one-period effect of Medicaid expan-

[9] Callaway and Sant'Anna (2021) does not allow for a continuous treatment variable. I thus unfortunately cannot implement this robustness check with the FQHC analysis.

sions on hospital FAPs (Panels D and E), though this effect promptly zeros out in the remaining post periods. [10]

5 Conclusion

Little is known about the relationship between private and public provisions of charity healthcare. By examining changes in non-profit hospitals' financial assistance spending levels and written policies following increases in public healthcare safety net provision, this paper provides important insights into the dynamics of public and private organizations in charity healthcare markets.

Overall, my analysis provides substantial evidence of public spending crowding out private spending on charity healthcare. I find that a one standard deviation increase in Federally Qualified Health Centers (FQHCs) per baseline uninsured results in a 9% decrease in non-profit hospital charity care. Additionally, I show that state-level Medicaid expansions lead to a 35% decrease in both non-profit hospital charity care and uncompensated care expenditures, with effects persisting over multiple years. This Medicaid analysis extends previous short-term studies on this topic by demonstrating the long-term impacts of public health insurance expansion on private charity care.

Despite significant changes in charity care levels, I find no evidence that increased public healthcare safety net provision affects non-profit hospitals' financial assistance policies; hospitals appear to simply allow their charity spending to fall with demand. I also establish that there is virtually no correlation between changes in these policies and hospital charity expenditures. These results raise questions about the role and effectiveness of non-profit hospitals' financial assistance policies, indicating a need for further research into policy-setting practices.

In conclusion, this paper demonstrates clear evidence of public spending displacing private charity care in the healthcare sector. As policymakers in the U.S. continue to grapple with healthcare reform, understanding these complex interactions between public and private providers will be crucial for designing effective and efficient safety net programs.

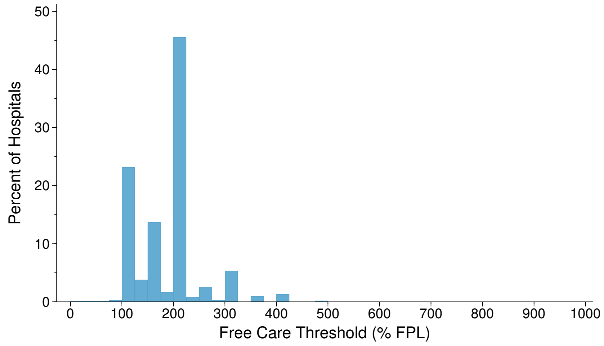
[10] Given the volatility of these estimates and the only marginal significance of the one-period effect, I recommend further robustness checks before interpreting the first-period Callaway and Sant'Anna (2021) estimates in these two panels as unbiased.

Table 1: Hospital Summary Statistics

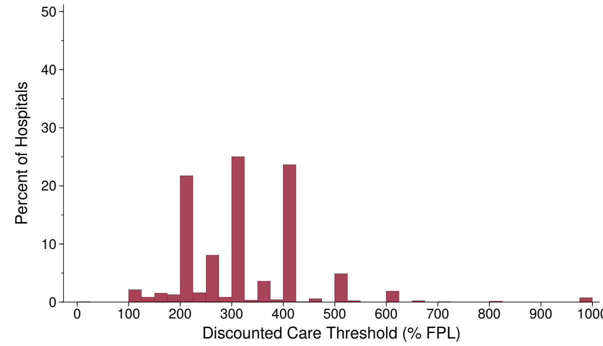
	(1) Mean	(2) SD	(3) N
Panel A. AHA			
# Staffed Beds	162.18	184.17	14548
# Annual Admissions	7,123.93	9,240.13	14548
# Annual Medicaid Discharges	1,438.05	2,435.95	14548
# Annual ED Visits	29,418.43	29,687.49	14548
Teaching Hospital?	0.36		14548
Church Affiliated Hospital?	0.21		14548
Sole Community Hospital?	0.08		14548
Hospital Has ED?	0.99		14535
Hospital Has Indigent Health Clinic?	0.21		12648
Panel B. IRS			
Annual Functional Expenses ($ million)	189.17	349.51	14542
Annual Revenue ($ million)	200.28	374.88	14548
Charity Care (% Expenses)	1.95	1.92	14197
Charity Care + Bad Debt (% Expenses)	6.55	4.83	13999
Community Benefits (% Expenses)	7.99	5.16	14430
Free Care Policy using FPL?	0.97		14372
Discounted Care Policy using FPL?	0.89		14389
Free Care Threshold (% FPL)	181.84	61.68	13927
Discounted Care Threshold (% FPL)	329.60	112.03	12701

Notes: Table shows summary statistics on non-profit hospitals for years 2010-2018 using data from the AHA Annual Surveys (Panel A) and the IRS Form 990 tax returns (Panel B). Sample includes only hospital organizations that contain one hospital facility which is a short-term acute care hospital.

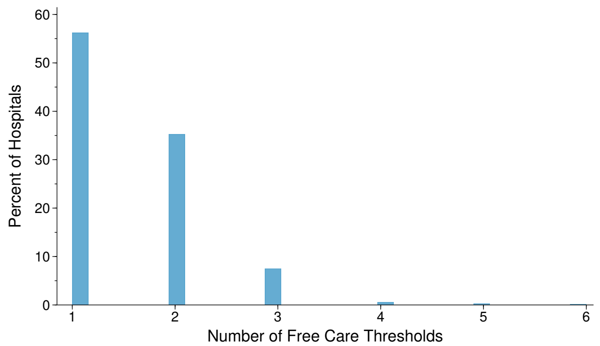
Figure 1: Hospital Charity Care Policies



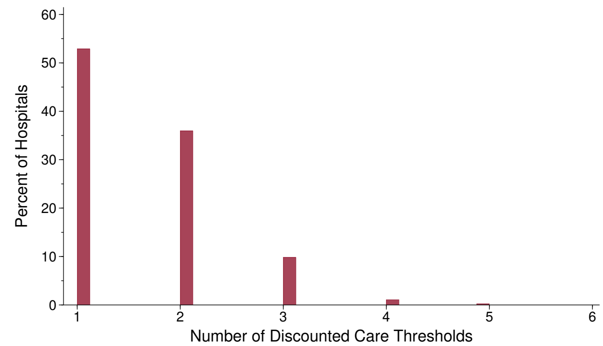
(a) Free Care Thresholds (2010)



(b) Discounted Care Thresholds (2010)



(c) # Free Care Thresholds per Hospital



(d) # Discounted Care Thresholds per Hospital

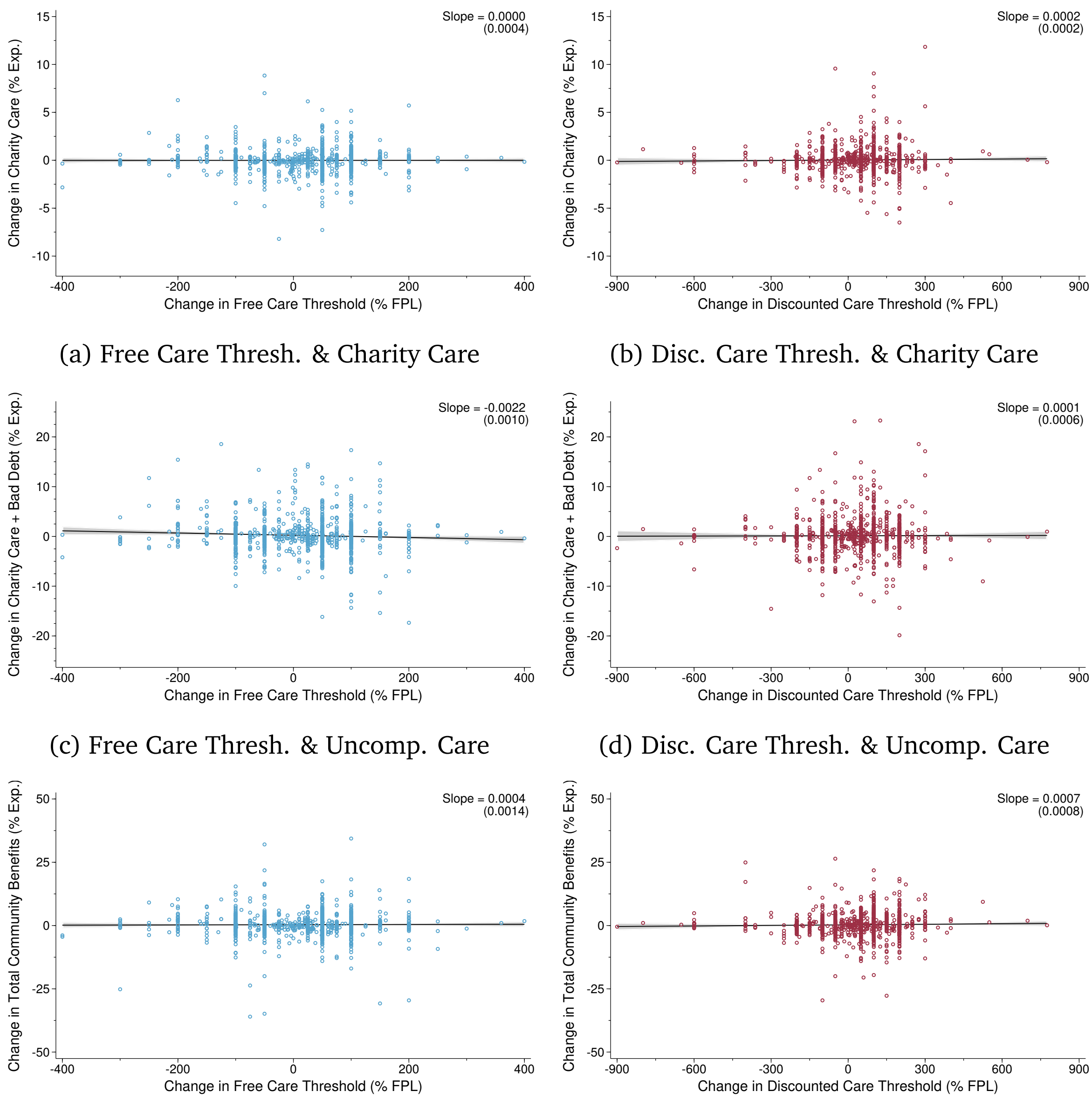
Notes: Panels A and B plot the distribution of free care and discounted care financial assistance policy (FAP) thresholds as a percent of the federal poverty line (FPL) across non-profit hospitals in 2010, respectively. Panels C and D plot the distribution of the number of unique free care FAP thresholds and discounted care FAP thresholds that each non-profit hospital has across the entire sample period (2010-2018), respectively. All panels show data from IRS Form 990 tax returns.

Table 2: Changes in Hospital Charity Care Policies (2010-2018)

	(1) Free Care Threshold	(2) Discounted Care Threshold
% of hospitals that change policy	43.79%	47.12%
Ave # changes, given at least one	1.23	1.27
(SD)	(0.54)	(0.52)
% of changes that are positive	64.92%	68.14%
Ave magnitude of positive changes (pp of FPL)	72.77 pp	120.74 pp
Ave magnitude of negative changes (pp of FPL)	-85.21 pp	-126.36 pp

Notes: Table shows summary statistics of changes in non-profit hospitals' free care and discounted care thresholds across sample years (2010-2018) using data from IRS Form 990 tax returns. Sample includes only hospital organizations that contain one hospital facility which is a short-term acute care hospital.

Figure 2: Changes in FAP Income Thresholds & Changes in Charity Levels



(a) Free Care Thresh. & Charity Care

(b) Disc. Care Thresh. & Charity Care

(c) Free Care Thresh. & Uncomp. Care

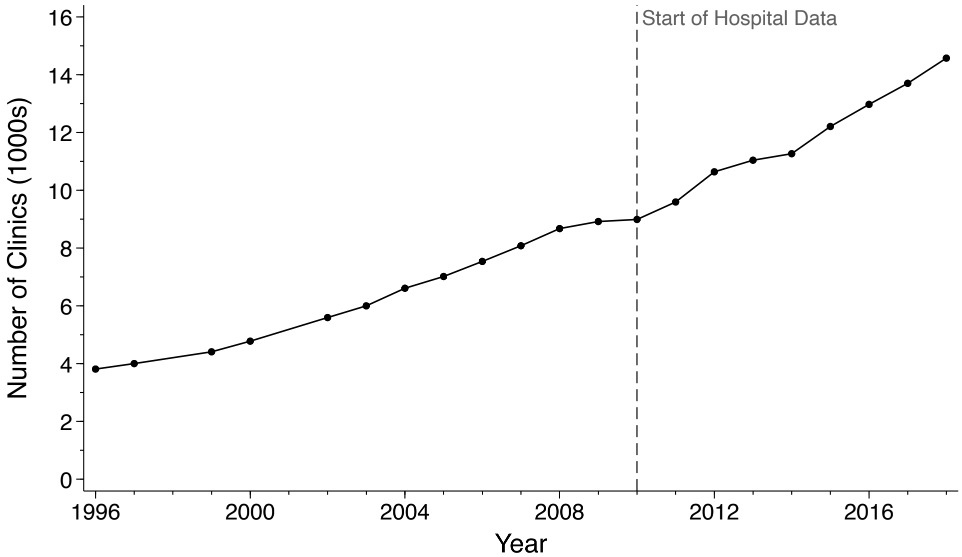
(d) Disc. Care Thresh. & Uncomp. Care

(e) Free Care Thresh. & Total Comm. Benefits

(f) Disc. Care Thresh. & Total Comm. Benefits

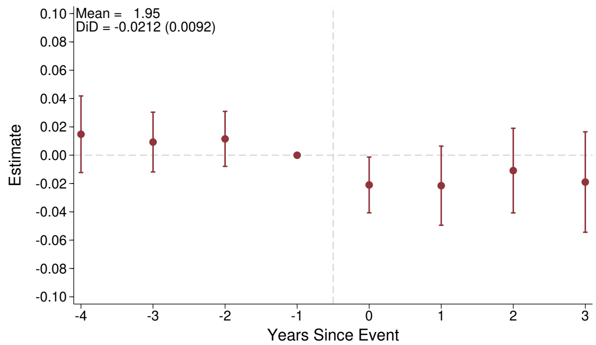
Notes: Figures plot the relationship between changes in non-profit hospital financial assistance policy (FAP) income thresholds as a percent of the federal poverty line (FPL) and changes in non-profit hospital charity levels (expressed as a percent of total hospital expenditures). Panels in the first column show changes in the free care threshold on the X-axis, while panels in the second column show changes in the discounted care threshold on the X-axis. Panels A and B show change in charity care on the Y-axis. Panels C and D show change in uncompensated care (i.e., charity care plus bad debt) on the Y-axis. Panels E and F show change in total community benefits on the Y-axis. Blue and red dots represent unique data points. Fitted regression lines (black) and 95% confidence intervals (shaded gray) are also included, with the slope and SE of the regression lines displayed in the top right hand corner of each panel. All panels show data from IRS Form 990 tax returns.

Figure 3: Number of FQHC Clinics

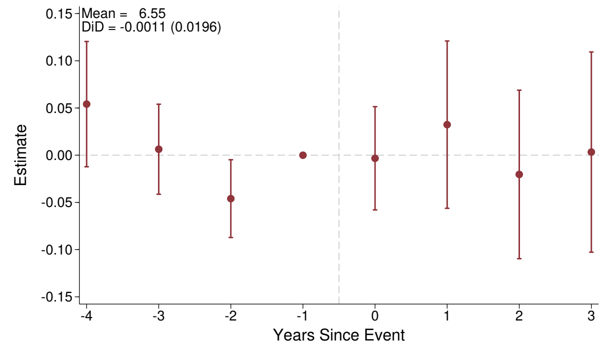


Notes: Figure plots the number of active federally qualified health center (FQHC) clinics in the U.S. in each year from 1996 to 2018, using data from the Uniform Data Set (UDS) and the Provider of Service (POS) files. The vertical dashed line at year 2010 shows the first year in which this paper's hospital data sample begins.

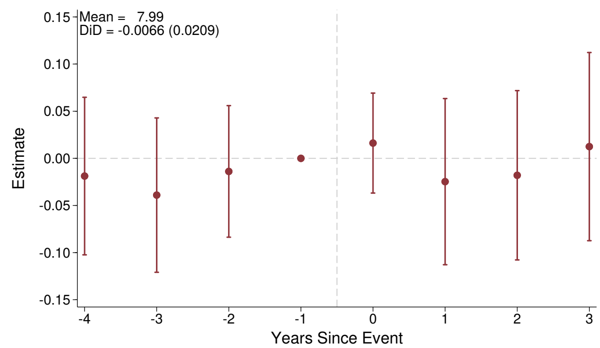
Figure 4: Effects of Clinics on Hospital Outcomes (County-Level)



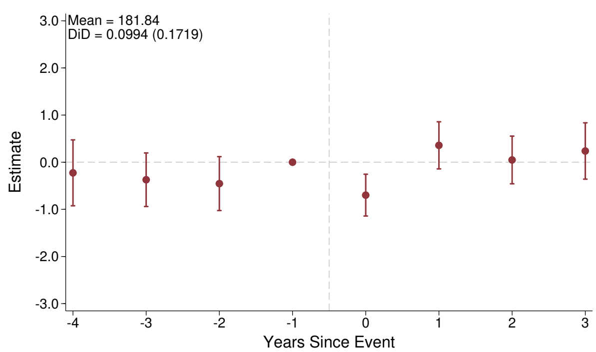
(a) Charity Care (% Expenses)



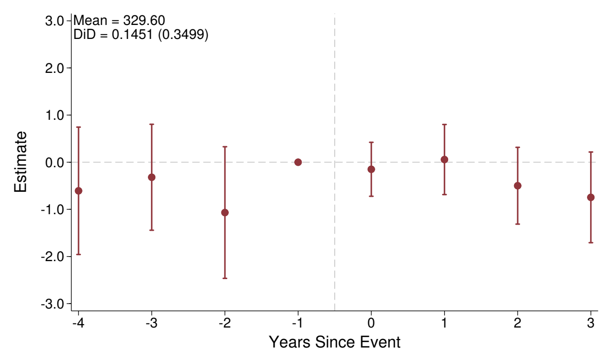
(b) Charity Care + Bad Debt (% Expenses)



(c) Total Community Benefits (% Expenses)



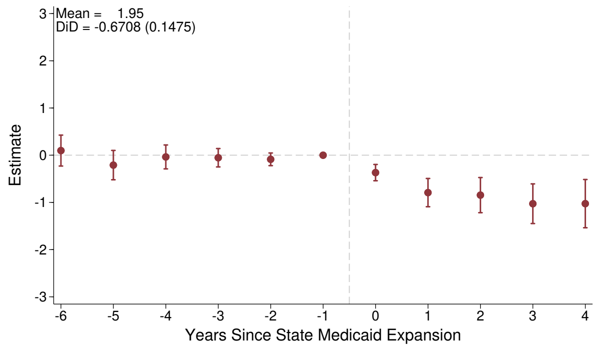
(d) Free Care Threshold (% FPL)



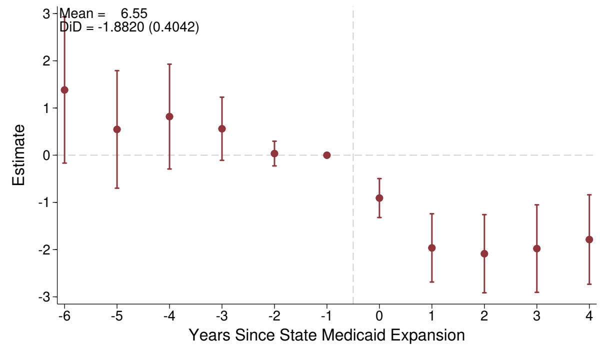
(e) Discounted Care Threshold (% FPL)

Notes: Figures plot the estimated coefficients β_r of Equation 3.2 as red dots with the lines representing 95% confidence intervals. County is used as the definition of a local area. Sample construction and controls are described in the main text.

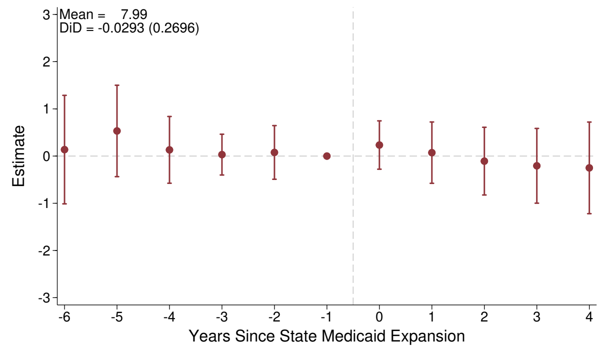
Figure 5: Effects of Medicaid Expansion on Hospital Outcomes



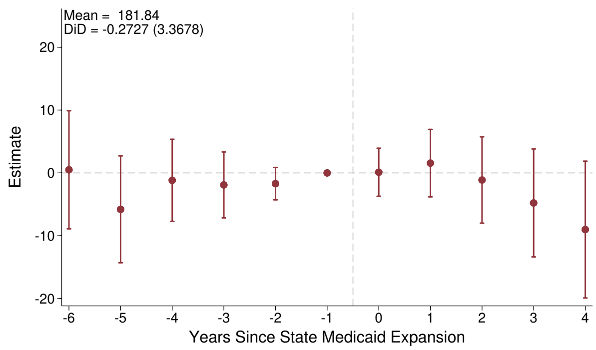
(a) Charity Care (% Expenses)



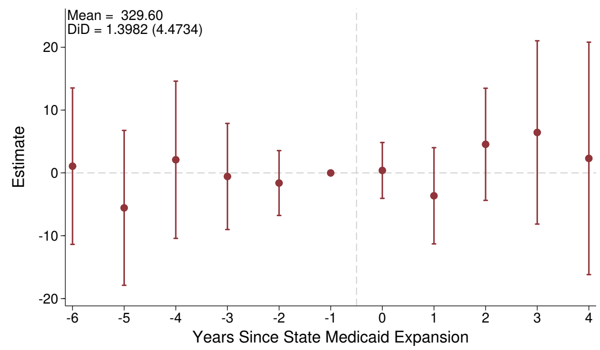
(b) Charity Care + Bad Debt (% Expenses)



(c) Total Community Benefits (% Expenses)



(d) Free Care Threshold (% FPL)



(e) Discounted Care Threshold (% FPL)

Notes: Figures plot the estimated coefficients β_r of Equation 4.1 as red dots with the lines representing 95% confidence intervals. Sample construction and controls are described in the main text.

Table 3: Clinic Presence Analysis (County-Level)

	(1) Charity Care (% Expenditures)	(2) Charity Care + Bad Debt (% Expenditures)	(3) Total Comm. Benefits (% Expenditures)	(4) Free Care Threshold (% FPL)	(5) Discounted Care Threshold (% FPL)
Panel A. Levels-Levels					
Number of Clinics per 10,000 Baseline Uninsured	-0.0212**	-0.0011	-0.0066	0.0994	0.1451
	(0.0092)	(0.0196)	(0.0209)	(0.1719)	(0.3499)
N	14197	13999	14430	13927	12701
Mean of Dep. Var.	1.95	6.55	7.99	181.84	329.60
Panel B. Logs-Logs					
LN[Number of Clinics]	-0.0783*	-0.0061	0.0330	-0.0087	0.0025
	(0.0415)	(0.0282)	(0.0288)	(0.0123)	(0.0108)
N	10228	10209	10341	10297	9409

Notes: Each cell represents a separate regression estimate from a specification with hospital and year fixed effects, controls for county-level population and unemployment rates, and standard errors clustered at the county level (i.e., a separate estimation of Equation 3.1). Standard errors are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

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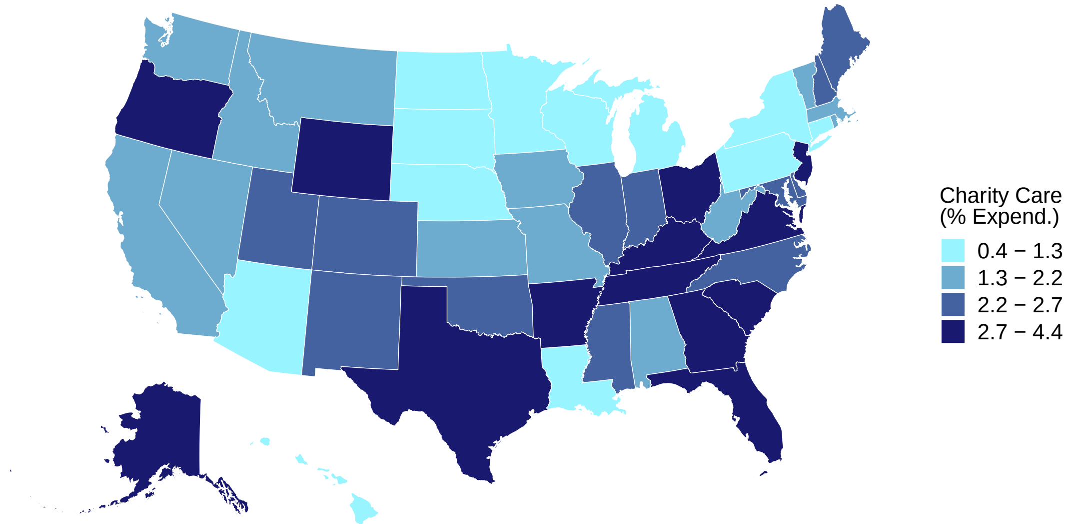
A Additional Figures & Tables

Table A1: Comparison of Hospital Sample to Full Hospital Population

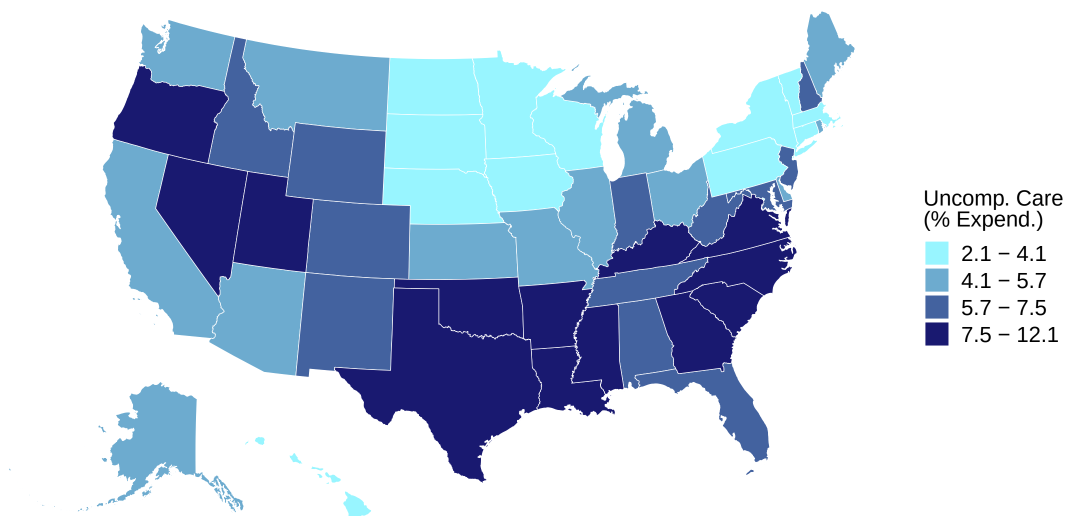
	(1) Mean of Paper's Sample	(2) Mean of Population	(3) t-stat for (1)=(2)
Panel A. AHA			
# Staffed Beds	162.18	189.12	-12.80
# Annual Admissions	7,123.93	8,672.35	-14.53
# Annual Medicaid Discharges	1,438.05	1,719.82	-10.52
# Annual ED Visits	29,418.43	34,107.34	-13.60
Teaching Hospital?	0.36	0.41	-8.40
Church Affiliated Hospital?	0.21	0.24	-6.33
Sole Community Hospital?	0.08	0.07	3.30
Hospital Has ED?	0.99	0.99	1.53
Hospital Has Indigent Health Clinic?	0.21	0.22	-2.54
Panel B. IRS			
Annual Functional Expenses ($ million)	189.17	289.34	-14.86
Annual Revenue ($ million)	200.28	306.77	-14.83
Charity Care (% Expenses)	1.95	1.98	-1.17
Charity Care + Bad Debt (% Expenses)	6.55	6.33	3.96
Community Benefits (% Expenses)	7.99	8.06	-1.23
Free Care Policy using FPL?	0.97	0.96	4.34
Discounted Care Policy using FPL?	0.89	0.88	2.59
Free Care Threshold (% FPL)	181.84	184.35	-3.64
Discounted Care Threshold (% FPL)	329.60	333.65	-3.08

Notes: Comparison of summary statistics from this paper's sample of non-profit hospitals to the full population of acute care community non-profit hospitals in the AHA Annual Surveys (Panel A) and to the full population of non-profit hospital tax returns in the IRS Form 990 data (Panel B) for 2010-2018. Column 1 presents the means for this paper's sample (which are also reported in Table 1), while Column 2 presents the means for the full population. Column 3 reports t-statistics from tests of hypotheses of equality across Columns 1 and 2.

Figure A1: Hospital Charity Care Provision by State (2010)



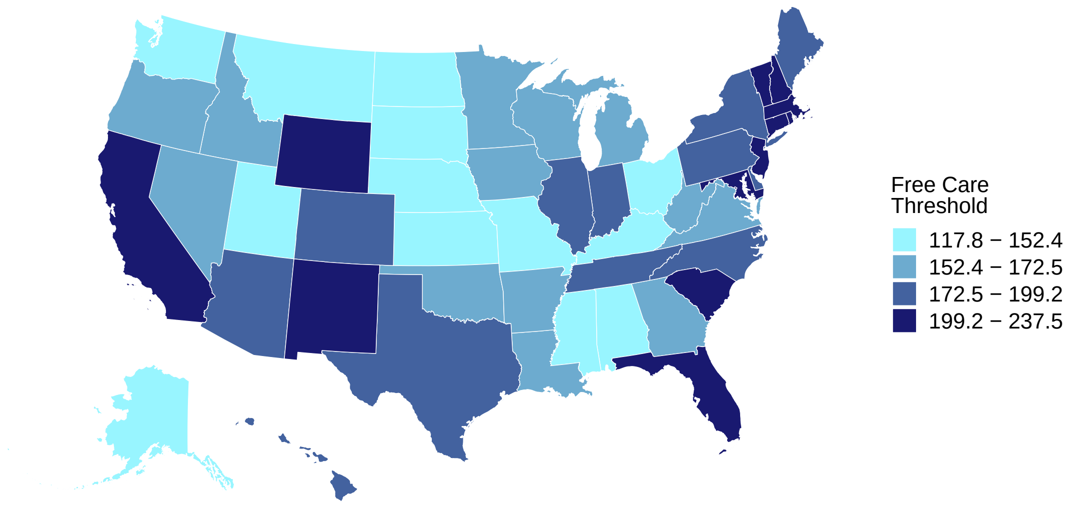
(a) Charity Care (% Expenses)



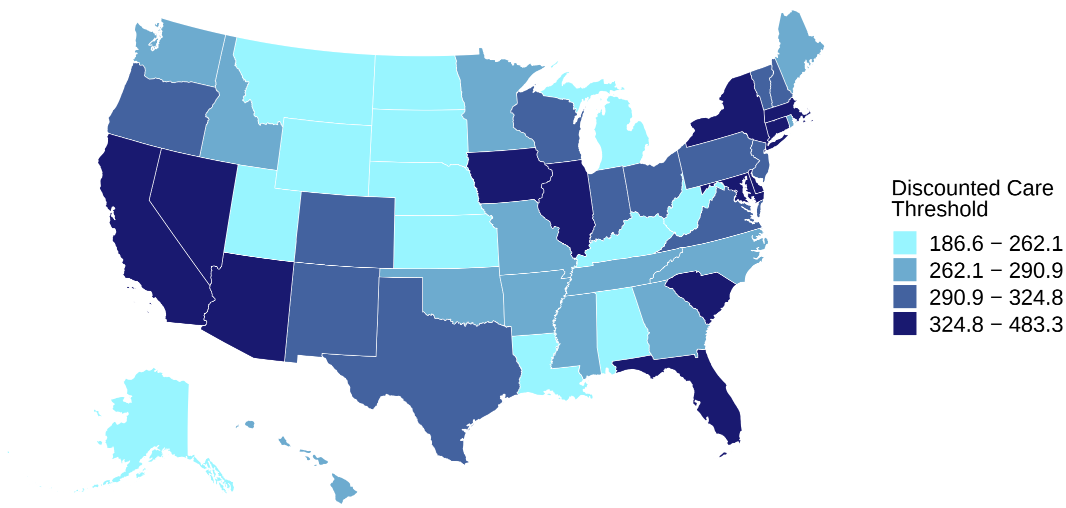
(b) Charity Care + Bad Debt (% Expenses)

Notes: Maps depict (A) average amount of charity care and (B) average amount of uncompensated care (charity care + bad debt), expressed as percentages of total non-profit hospital expenditures, in each U.S. state in 2010.

Figure A2: Hospital Charity Care Policy by State (2010)



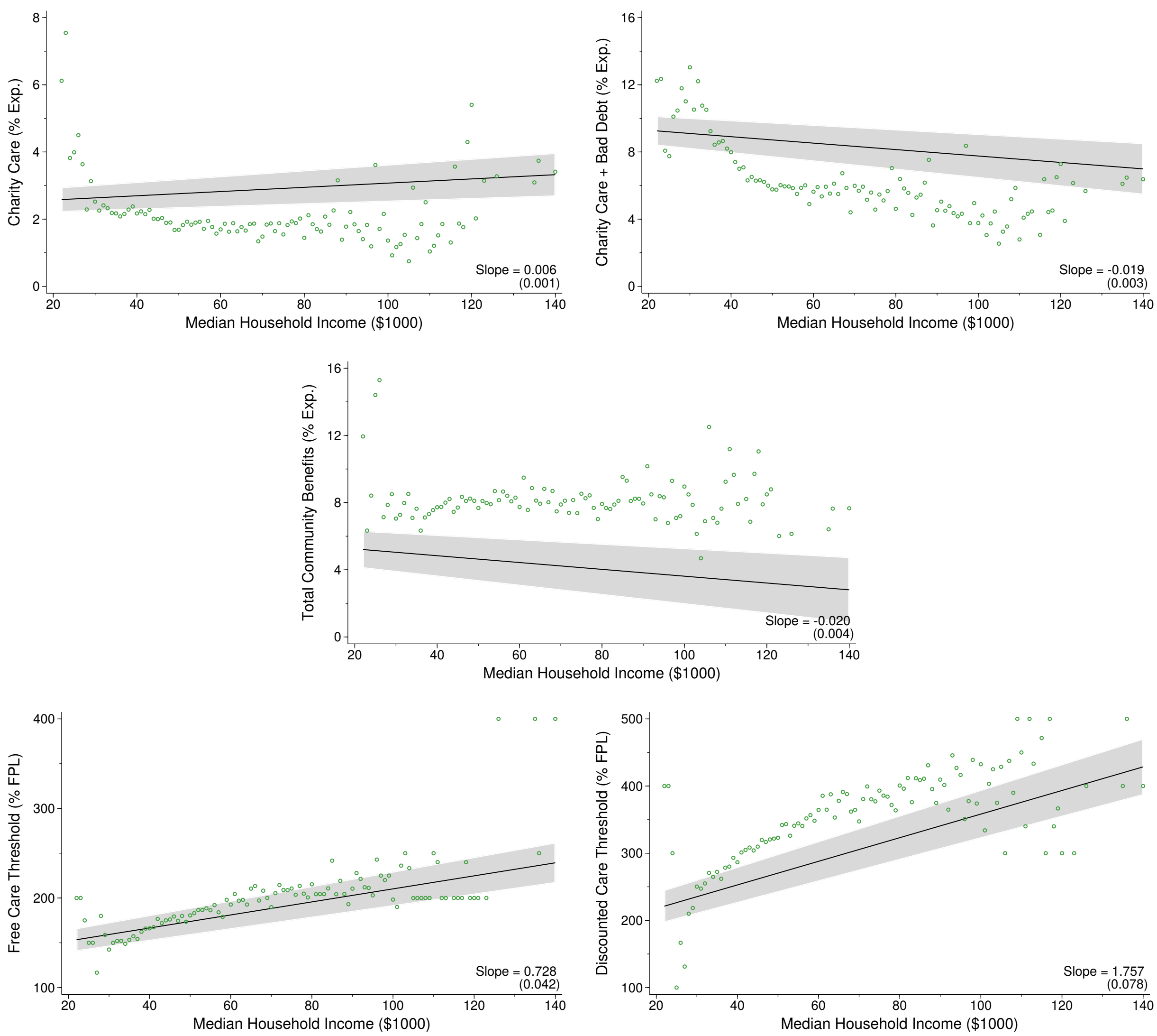
(a) Free Care Threshold (% FPL)



(b) Discounted Care Threshold (% FPL)

Notes: Maps depict (A) average free care thresholds and (B) average discounted care thresholds, expressed as percentages of the federal poverty level (FPL), in each U.S. state in 2010.

Figure A3: Median Household Income & Hospital Charity Care



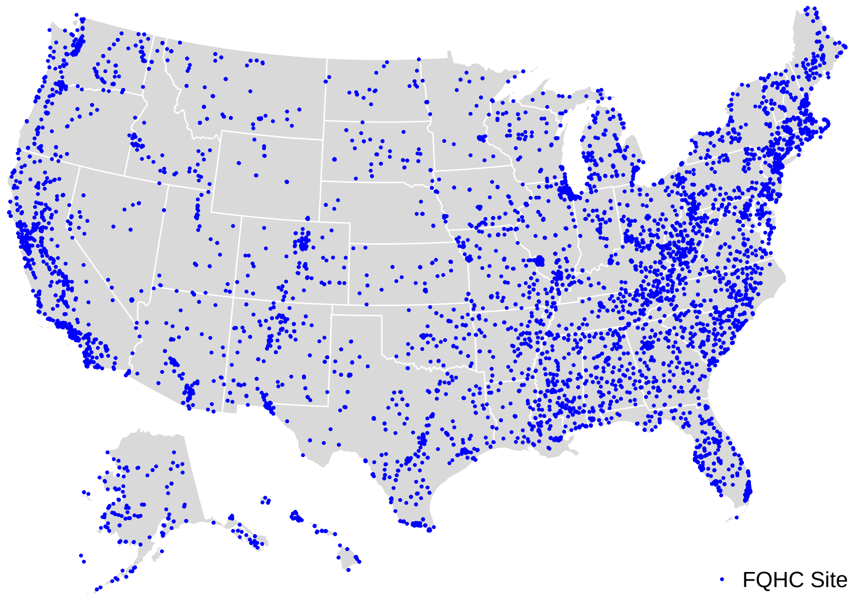
Notes: Median household income at county-by-year level is from the U.S. Census SAIPE. To construct this figure, state-level and year-level variation in the dependent variable is partialled out. Each panel then plots the regression line (black) and the 95% confidence interval (gray shaded region). The green data points were constructed by creating bins for each unit increment ($1,000) of income. The data points show the mean charity level/threshold for each bin of income.

Table A2: FQHC Organization Summary Statistics (2010-2018)

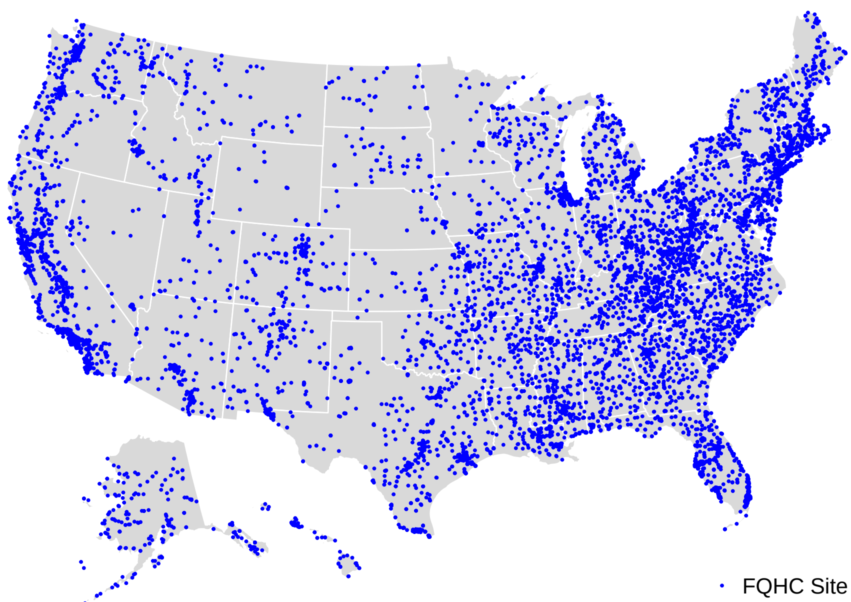
	(1) Mean	(2) SD	(3) N
Number of Sites	7.58	8.75	11017
Number of Patients	18,612.84	21,920.53	11128
Total Grants	5,008,844.06	5,777,588.45	11140
Section 330 Grants	2,689,237.20	2,440,268.44	11131
Grants for health	2,557,512.32	2,297,551.71	11131
Grants for capital	178,743.10	687,623.77	8203
Other Federal Grants	526,584.57	1,072,736.65	10311
State Grants	584,801.39	1,325,300.55	9755
Local Grants	480,207.43	1,489,935.36	8969
S&L Grants for Indigent	514,701.03	2,155,609.73	8629
Private Grants	586,579.42	1,766,139.80	10198

Notes: Summary statistics for FQHC organizations from 2010 to 2018 using UDS data. Dollars are nominal.

Figure A4: Clinic Locations Across U.S.



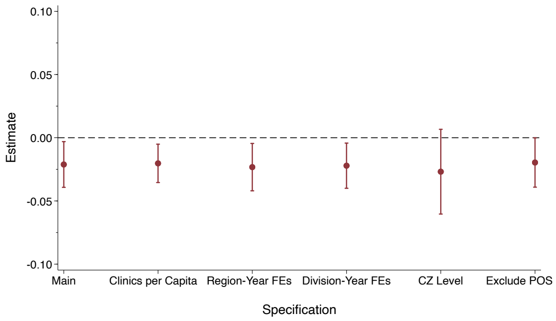
(a) Clinics in 2010



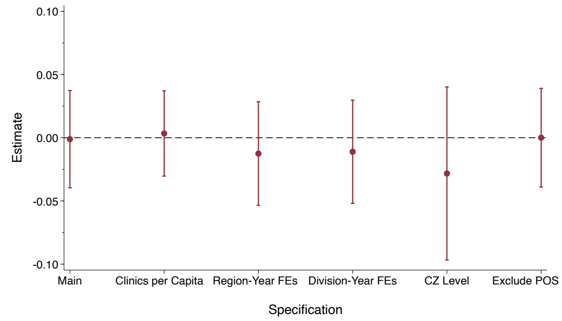
(b) Clinics in 2018

Notes: Maps depict the locations of FQHC clinics in 2010 (Panel A) and 2018 (Panel B) using data from UDS and POS.

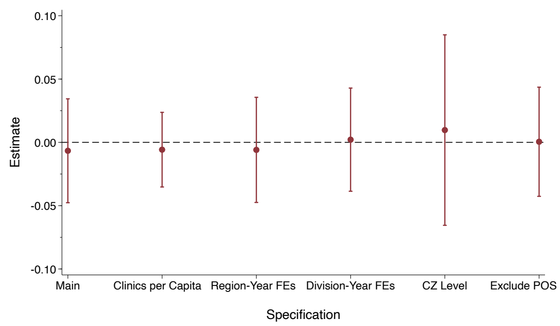
Figure A5: Clinic Presence Analysis - Robustness



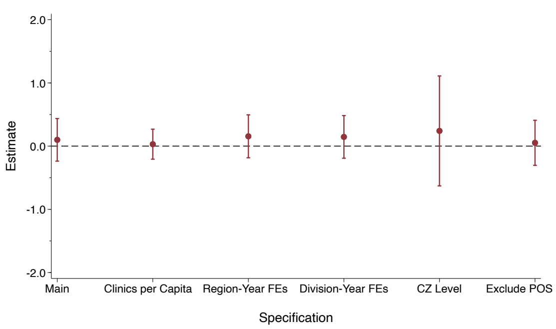
(a) Charity Care (% Expenditures)



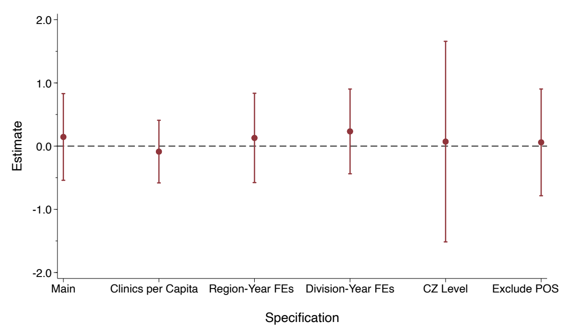
(b) Charity Care + Bad Debt (% Expenditures)



(c) Total Community Benefits (% Expenditures)



(d) Free Care Threshold (% FPL)



(e) Discounted Care Threshold (% FPL)

Notes: Figures test robustness of the results presented in Table 3 to slight changes in the regression specification: (1) scaling number of clinics by county-level population instead of county-level baseline uninsured; (2) replacing year fixed effects with Census region-by-year FEs; (3) replacing year fixed effects with Census division-by-year FEs; (4) measuring clinic presence at the CZ level rather than the county level; and (5) excluding POS data from the analysis and thus relying only on the UDS for clinic information. Red dots are the estimated coefficients, while bars represent the 95% confidence intervals.

Table A3: Clinic Presence Analysis (County-Level) - Heterogeneity

	(1) Charity Care (% Expenditures)	(2) Charity Care + Bad Debt (% Expenditures)
Panel A. Teaching Institution		
Number of clinics per uninsured	-0.0189**	0.0089
	(0.0080) (0.0179)	
Number of clinics per uninsured * interaction	-0.0076	-0.0304*
	(0.0059)	(0.0165)
Panel B. Church-Affiliated		
Number of clinics per uninsured	-0.0186***	0.0116
	(0.0066)	(0.0173)
Number of clinics per uninsured * interaction	-0.0130	-0.063392
	(0.0282)	(0.0390)
Panel C. Sole Community Provider		
Number of clinics per uninsured	-0.0218***	0.0001
	(0.0080)	(0.0170)
Number of clinics per uninsured * interaction	0.0229	0.0550
	(0.0197)	(0.0354)
Panel D. In County with Above Baseline Median Percentage of Population under FPL		
Number of clinics per uninsured	0.0053	0.0225
	(0.0094)	(0.0191)
Number of clinics per uninsured * interaction	-0.0334**	-0.0251
	(0.0132)	(0.0279)
Panel E. Has ED		
Number of clinics per uninsured	-0.0125	0.0011
	(0.0569)	(0.0510)
Number of clinics per uninsured * interaction	-0.0077	0.0021
	(0.0565)	(0.0491)
Panel F. Operates Indigent Health Clinic		
Number of clinics per uninsured	-0.0178**	0.0038
	(0.0080)	(0.0199)
Number of clinics per uninsured * interaction	0.0057	0.0235
	(0.0080)	(0.0219)
N	14197	13999
Mean of Dep. Var.	1.95	6.55

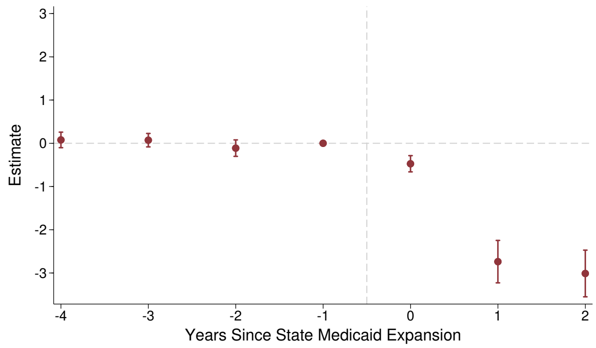
Notes: Each panel+column combination represents a separate regression estimate from a specification with hospital and year fixed effects, controls for county-level population and unemployment rates, and standard errors clustered at the county level (i.e., a separate estimation of Equation 3.1 with heterogeneity allowed). Standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Medicaid Expansion - Static Regression

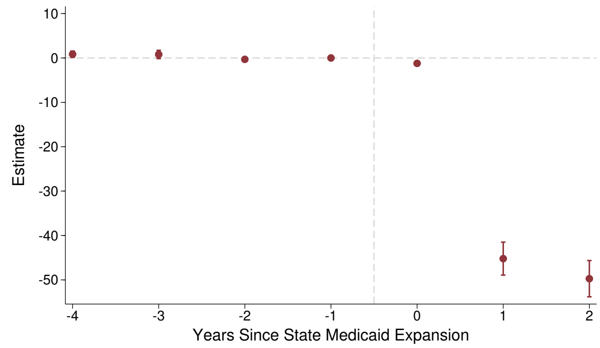
	(1) Charity Care (% Expenditures)	(2) Charity Care + Bad Debt (% Expenditures)	(3) Total Comm. Benefits (% Expenditures)	(4) Free Care Threshold (% FPL)	(5) Disc. Care Threshold (% FPL)
Expansion*Post	-0.6708***	-1.8820***	-0.0293	-0.2727	1.3982
	(0.1475)	(0.4042)	(0.2696)	(3.3678)	(4.4734)
N	14197	13999	14430	13927	12701

Notes: Static version of Equation 4.1. Each cell represents a separate regression estimate from a specification with hospital and year fixed effects, controls for county-level population and unemployment rates, and standard errors clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01.

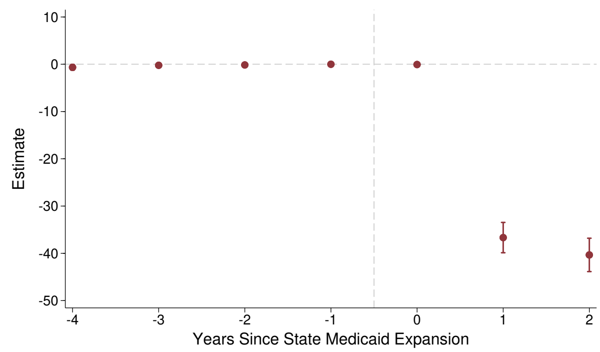
Figure A6: Effects of Medicaid Expansion on Hospital Outcomes - Callaway and Sant'Anna



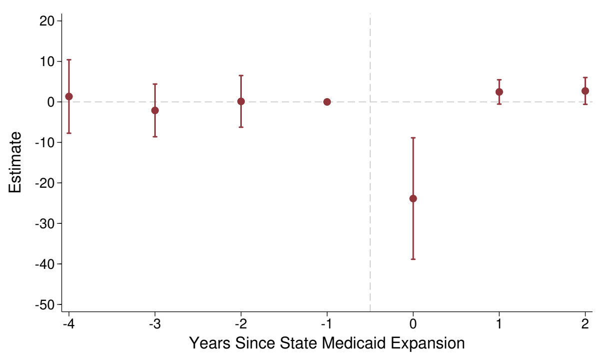
(a) Charity Care (% Expenses)



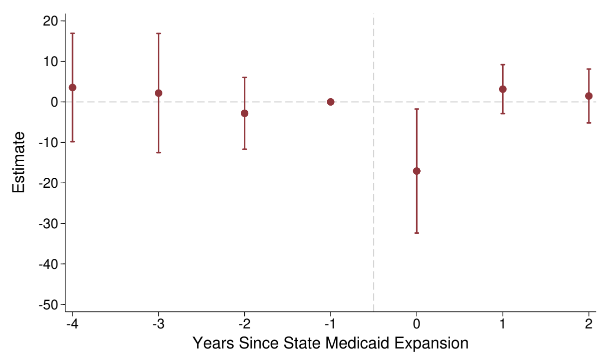
(b) Charity Care + Bad Debt (% Expenses)



(c) Total Community Benefits (% Expenses)



(d) Free Care Threshold (% FPL)



(e) Discounted Care Threshold (% FPL)

Notes: Figures plot the estimated coefficients β_r the Callaway and Sant'Anna (2021) version of Equation 4.1 as red dots with the shaded regions representing 95% confidence intervals. Sample construction and controls are described in the main text.

B Additional Details on Non-Profit Hospital Charity

Non-profit hospitals provide a significant amount of uncompensated care to uninsured and low-income individuals. To determine which patients are eligible for charity care, most non-profit hospitals have written financial assistance policies (FAPs) that consist of financial criteria to qualify for assistance. These criteria typically involve income thresholds for free or discounted care that are benchmarked to the federal poverty level (FPL). If a patient has a family income under a certain percentage of the FPL based on her family size (e.g., 150% of the FPL, which is $39,750 for a family of four), then a hospital's FAP states that the patient is not responsible for any amount of her hospital bill that is not covered by insurance. If a patient has a family income under a slightly higher percentage of the relevant FPL (e.g., 200% of the FPL), then a hospital's FAP states that the patient is eligible for discounts on any amount of her hospital bill that is not covered by insurance. Typically, both uninsured and insured patients can qualify for free or discounted care under these policies. Note that in addition to income requirements, some hospitals have asset requirements for eligibility; due to data limitations, however, I will only be able to analyze income thresholds.

Why non-profit hospitals provide any charity care at all is most frequently answered with (1) federal regulations and (2) preferential tax treatment. EMTALA requires all Medicare-participating hospitals with EDs to screen and treat the emergency medical conditions of all arriving patients until these conditions are stabilized. This screening and treatment must be done in a non-discriminatory manner, regardless of factors such as a patient's ability to pay or health insurance status.[11] However, while EMTALA requires hospitals to serve uninsured and low-income patients, the federal regulation does not preclude a hospital from charging patients for services provided in the ED. Hospitals can—and very often do—bill patients who receive ED care regardless of insurance status or income.

An additional explanation for why hospitals provide charity care is that federal tax law motivates this behavior. Prior to 2016, this motivation was not an explicit requirement. To be designated as non-profit organizations under Section 501(c)(3) of the federal Internal Revenue Code (and to receive the exemption from federal income tax that comes with such a designation)[12] hospitals were simply required to meet a "community benefit standard" of charitably

[11]There is some evidence that the uninsured receive less intensive ED care than the insured Doyle (2005) and that EMTALA violations are both under-reported and infrequently penalized Terp et al. (2017).

[12]In addition to federal corporate income tax exemptions, non-profit hospitals are also exempt from state corporate income tax, state sales tax, and local property tax. They also benefit from tax-exempt bond financing and from the ability to receive charitable contributions that are tax-deductible to donors. Herring, Gaskin, Zare, and Anderson (2018) estimate that the average value of tax exemption to a non-profit hospital in 2012 was $11.3 million, or 5.9% of total hospital expenses.

promoting health to a broad class of persons in their communities. This standard could be met in a number of different ways, including through charity care, medical research, or teaching; crucially, however, the standard did not explicitly require non-profit hospitals to provide any charity care to uninsured or low-income patients. Despite this lack of a mandate to provide charity care, nearly all non-profit hospitals had FAPs in place and provided at least some charity to their uninsured and low-income patients (Nikpay and Ayanian, 2015). Beginning in 2016, non-profit hospitals were explicitly required to provide charity care for the first time in recent history following the implementation of additional rules under Section 501(r) of the Internal Revenue Code, including a requirement that non-profit hospitals establish written FAPs.[13] It is noteworthy that under both the pre-2016 and post-2016 standards, much is still left to the organization's discretion. While non-profit hospitals are now federally required to have a written FAP for charity care, there is no federally specified level of charity care or overall community benefits that they must provide, and they have full control over the eligibility thresholds that they set for free and discounted care. As a result, charity care levels and policies vary widely.

Since both federal regulations and preferential tax treatment are insufficient to explain the breadth and variation in non-profit hospital charity care, the questions of why non-profit hospitals provide charity care and what factors motivate changes to their provisions and policies remain largely unanswered. As stated in the introduction, few previous studies in the economics and healthcare literature have focused on hospital charity care, and even fewer have analyzed the drivers of hospital FAPs. Sachs (2019a) is the only paper other than this one to investigate possible factors that influence non-profit hospitals' charity care policies, finding that FAPs appear to respond to state-level regulations that are enforced by court actions but not to state-level Medicaid expansions within a one-year time frame. I add to this literature by looking at the effect of state-level Medicaid expansions beyond a one-year time frame and, more crucially, by evaluating the effect of public in-kind safety net healthcare provision on nearby non-profit hospitals' charity.

The IRS Form 990 tax returns allow me to overcome two challenges to measuring hospital charity care using other sources of data. First, expenditures in other sources of data do not effectively differentiate between charity care, Medicaid shortfalls, and bad debt.[14] Second, all

[13]But not for the first time in American history. Prior to 1969, the IRS required non-profit hospitals to provide free or highly discounted care to low-income patients in order to retain their tax-exempt status. This policy was changed in response to the enactment of Medicare and Medicaid, which policymakers believed would lessen the need for charity care in hospitals across the country (Rosenbaum, Kindig, Bao, Byrnes, and O'Laughlin, 2015).

[14]Other national sources on hospital uncompensated care include the AHA Annual Survey and Medicare cost reports (HCRIS). Both the AHA and the Medicaid and CHIP Payment and Access Commission explicitly caution against separately defining charity care and bad debt using their data, stating that their reports are not audited and the distinction may not be consistently reported across hospitals.

other sources of data on hospital charity care only include information on spending rather than information on both spending and policies. Given the relative newness of Schedule H in these returns, which was established in 2009, Young, Chou, Alexander, Lee, and Raver (2013) check the validity of Schedule H's community benefit and bad debt measures against other sources including AHA, public state government, and proprietary hospital data. The authors find that the Schedule H data is consistent with these other sources.