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Federal Assistance and Rural Hospital Closings: The Impact of the USDA Community Facilities Program

Anil Rupasingha and Julia Cho

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Abstract

Rural hospital closings in the United States continue to be a major concern for rural development stakeholders. Numerous studies have shown that the primary cause of rural hospital closures is severe financial stress. The Federal Government, through various agencies, administers multiple programs that provide financial support for rural hospitals. The Community Facilities (CF) Program administered by USDA Rural Development is one of the major Federal programs that provides financial assistance to rural hospitals. The authors studied the impact of the CF Program on rural hospital closures. They combined program data obtained from USDA and National Establishment Time-Series data that identifies rural hospitals, the hospitals' existence over time, closures, several hospital-related characteristics, and location information. Before conducting the statistical analysis, the authors created a synthetic experiment by matching rural hospitals that received program funding to those that did not, in terms of several hospital-level and area characteristics. The study found a statistically significant association between CF Program funding and a reduced likelihood of rural hospital closure.

Keywords: rural hospitals, hospital closure, Community Facilities Program

About the Authors

Anil Rupasingha is a research agricultural economist at USDA, Economic Research Service. Julia Cho is a social science analyst at USDA, Rural Development.

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A report summary from the Economic Research Service *January 2025*

Federal Assistance and Rural Hospital Closings: The Impact of the USDA Community Facilities Program

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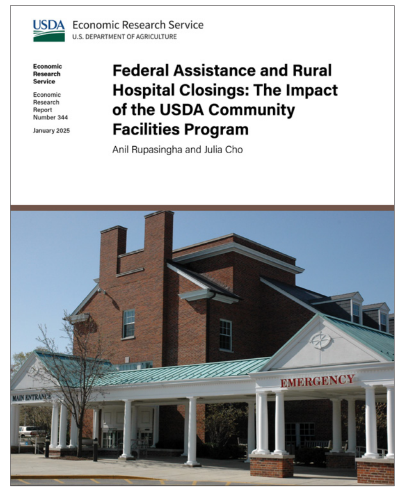


What Is the Issue?

Rural hospital closings in the United States continue to be a concern for policymakers, community development practitioners, and rural residents. The authors of this report found that 146 hospitals in nonmetro counties in the United States have either completely closed or been converted to non-acute care (i.e., stopped providing general, short-term, acute inpatient care) since 2005. Of the 146 closures, 81 were complete hospital shutdowns, with the remaining institutions undergoing "hospital conversions" that eliminated inpatient services but kept other services (e.g., emergency care, outpatient care, primary care, or urgent care) operational. Compared with their urban counterparts, U.S. rural hospitals face financial stress due to several unique conditions: Hospitals in rural areas are usually smaller, more vulnerable to fluctuations in the economy, and have lower occupancy rates. As a result, their profit margins are generally lower compared with those of urban hospitals. The Federal Government, through various agencies, administers multiple policies and programs that provide financial support for rural hospitals. The Community Facilities (CF) Program is administered by USDA, Rural Development and comprises one of the major Federal programs providing financial assistance to rural hospitals. Despite the investments by these programs and the length of time they have been active (since 1972), the authors could find only one published study that investigated their impact. The objective of the present study is to investigate the impact of the CF Program on rural hospital closures.

What Did the Study Find?

The authors found evidence that investments by the CF Program have helped recipient hospitals survive longer than a comparison group of similar nonrecipient hospitals in nonmetro counties; the probability of survival of similarly situated hospitals is higher for those that received CF funding than those that did not. When accounting for the year of program investments after 2000, hospital-specific observable factors (e.g., age and size) and unobservable factors (e.g., revenue and number of beds), the program-recipient hospitals in nonmetro counties were 94 percent less likely to close 6 years after the receipt of funding than were the group of similar nonrecipient hospitals. The effect of program support on hospital survival dropped with time; program recipients were 90 percent less likely to fail than nonrecipients after 8 years, and 88 percent less likely to fail after 10 years. Due to several limitations in the estimation approach and data, these findings should be evaluated with caution. These limitations include the incomplete capture of hospital-level attributes in the business data, the potential confounding influence of other Federal financial programs, the exclusion of newly constructed hospitals from the sample, the inability to differentiate between hospital closures and conversions (cessation of inpatient services), and inherent limitations of the exact matching technique employed.

How Was the Study Conducted?

To estimate the impact of the CF Program on rural hospital survival, administrative data from USDA's Rural Housing Service were combined with establishment-level data from the National Establishment Time-Series database. The empirical analysis was based on estimating a discrete-time proportional hazard model of hospital closures on a matched sample of hospitals that provided a valid counterfactual. The matched sample was obtained using exact matching methods and required that both program-recipient hospitals and nonrecipient hospitals be in the same State and same Rural-Urban Continuum Code, of the same establishment-type category, the same age group, and the same employment size during at least 3 years prior to the CF Program implementation.

Federal Assistance and Rural Hospital Closings: The Impact of the USDA Community Facilities Program

Introduction

Policymakers, community development professionals, and rural communities in the United States are becoming increasingly concerned about the closing of rural[1] hospitals (AHA, 2019; Alexander & Richards, 2023). The U.S. Federal Government has implemented several programs to help rural hospitals overcome their financial challenges. The objective of this report was to assess the impact of one such initiative, the Community Facilities (CF) Program, administered by USDA, on rural hospital closures. The North Carolina Rural Health Research Program (NC RHRP) developed a risk measure called the Financial Distress Index (FDI) in 2016 to identify hospitals at high risk of financial distress (Thomas et al., 2019).[2] This measure showed that the percentage of rural hospitals expected to face financial difficulties rose over time (from 7.1 percent in 2015 to 9.2 percent in 2019), with the largest increases occurring in the census regions of the South and Northeast. The Chartis Center for Rural Health, using data from 2010, stated that more than 450 of the country's rural hospitals were at risk of closing (Topchik et al., 2020). According to the center's report, the States that experienced the highest number of rural hospital closures since 2010 were in the South. These States included Texas (20 closures), Tennessee (12), Oklahoma (7), Georgia (7), Alabama (6), and Missouri (6). Figure 1, which is based on the data compiled by the Cecil G. Sheps Center for Health Services Research, shows that since 2005, the rural hospital closures involved 146 hospitals[3] [4] across nonmetro counties, with the years 2019 and 2020 reporting the highest number of closures (15 each year). Of the 146 closures, 81 were total hospital shutdowns, with the remaining institutions undergoing "hospital conversions," ceasing to offer inpatient services but keeping some services operational. Although the number of rural hospital closures slowed in some years during this period (in 2010, 2015, 2017, and 2021), the closures have started rising again since 2022. Rural hospitals received significant provider relief money ($15 billion as of February 2021) and

[1] In this study, the term "rural" or "nonmetro" (used interchangeably) is used based on Rural–Urban Continuum Codes (RUCC) (2003) developed by the USDA, Economic Research Service and based on the U.S. Office of Management and Budget (OMB) delineation of metro areas. RUCC classifies counties into three metro categories based on population size and six nonmetro categories based on their degree of urbanization and adjacency to a metro area. RUCC codes 1, 2, and 3 are considered "metro," and RUCC codes 4, 5, 6, 7, 8, and 9 are considered "nonmetro" or rural. The authors used this definition when drawing on other data sources for their own calculations. For example, when they used data from the Cecil G. Sheps Center for Health Services Research at the University of North Carolina, they used RUCC codes 4–9 to describe rural/nonmetro areas. The Sheps Center uses USDA Rural-Urban Commuting Area (RUCA) codes to classify rural hospitals. Their definition of rural includes any nonmetro county census tracts with RUCA codes 4–10, or large area metro census tracts of at least 400 square miles with a population density of 35 residents or less per square mile with RUCA codes 2–3. The Community Facilities (CF) Program defines eligible rural areas as cities, villages, townships, and towns, and federally recognized Tribal lands with no more than 20,000 residents, based on the latest U.S. Census data.

[2] The FDI model forecasts are based on several key factors: hospital financial performance, Government reimbursement, organizational characteristics, and market characteristics.

[3] This information is based on data compiled by the Cecil G. Sheps Center for Health Services Research (accessed February 26, 2024). Based on their definition of a rural hospital, the total number of hospitals closed during the same period was 191.

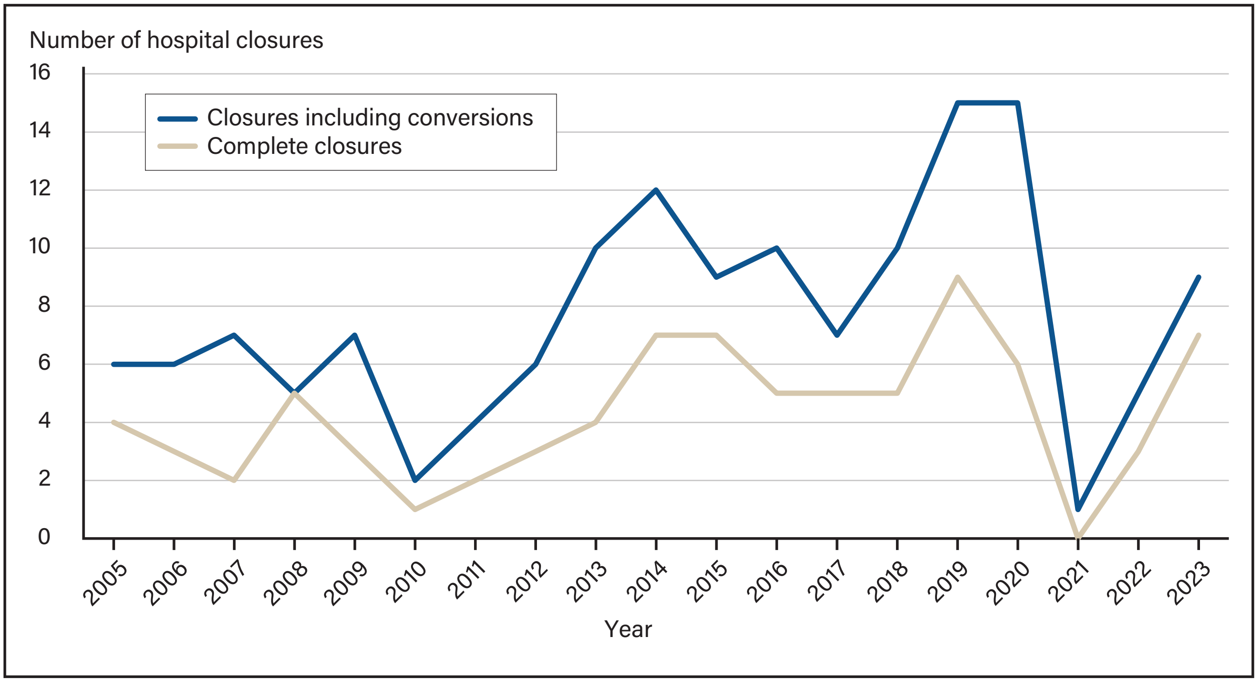
[4] Sheps Center classifies hospital closures into two categories: complete closures and converted closures. A facility that no longer provides health services is considered a complete closure. A hospital that closed its inpatient unit but continued to provide other health services is considered a converted closure.

other pandemic support during the Coronavirus (COVID-19) pandemic, and this may have contributed to the decline in closures in 2021 by keeping at-risk rural hospitals financially viable (Pink et al., 2022).

Based on USDA, Economic Research Service (ERS) Rural-Urban Continuum Codes (RUCCs), 66 percent of closed hospitals in nonmetro counties were in counties adjacent to a metro area (RUCCs 4, 6, and 8 in table 1). The rest of the closed hospitals in nonmetro counties were in remote (nonadjacent) nonmetro counties. Figure 2 shows that these closures are mostly concentrated in the southeastern and southwestern parts of the United States. A regional breakdown based on the Bureau of Economic Analysis (BEA) classification[5] for these closures (table 2) shows that a majority (44 percent) occurred in the Southeast region, followed by the Plains (19 percent) and Southwest (17 percent).

Figure 1

Rural hospital closures in nonmetro counties (RUCCs 4–9), 2005–23



RUCCs = Rural-Urban Continuum Codes.

Note: This chart shows rural hospital closures for nonmetro counties between 2005 and 2023. The total closures (blue line) include both completely closed and conversions (remained open to provide other health services).

Source: USDA, Economic Research Service data as of January 2024 from the Cecil G. Sheps Center for Health Services Research, University of North Carolina.

[5] Information on U.S. Department of Commerce, Bureau of Economic Analysis (BEA) regions, including States in each region, comes from BEA's Statistical Areas web page (accessed March 4, 2024).

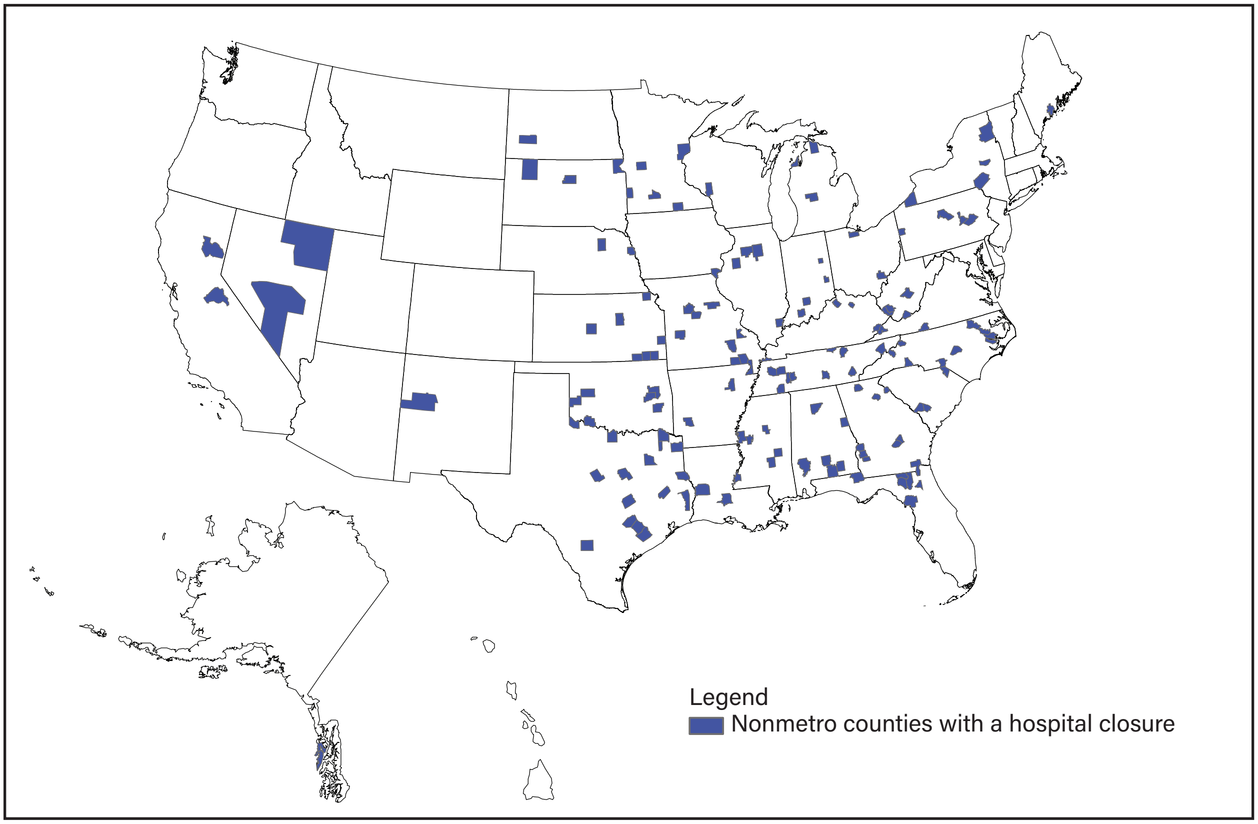
Table 1
Rural hospitals closures by nonmetro Rural-Urban Continuum Code (RUCC), 2005–23

	Closed/Converted		Completely closed	
RUCC	Number	Percent	Number	Percent
4	31	21	11	14
5	11	8	6	7
6	52	36	35	43
7	24	16	14	17
8	13	9	8	10
9	15	10	7	9
Total	146	100	81	100

Note: Based on 2003 USDA, Economic Research Service (ERS) Rural-Urban Continuum Codes (RUCCs).

Source: USDA, ERS calculations using RUCC codes based on data (as of January 2024) from the Cecil G. Sheps Center for Health Services Research, University of North Carolina.

Figure 2
Hospital closures in nonmetro (RUCCs 4–9) counties, 2005–23



RUCCs = Rural-Urban Continuum Codes.

Note: This map presents hospital closure data (permanently closed and converted) for nonmetro counties (RUCCs 4–9) between 2005 and 2023.

Source: USDA, Economic Research Service calculations based on hospital closure data for nonmetro counties as of January 11, 2024, from the Cecil G. Sheps Center for Health Services Research, University of North Carolina.

Table 2
Number of all hospital closures in nonmetro counties (RUCCs 4–9) by BEA region, 2005–23

Region	All closures	Percent of closures by region
Far West	5	3
Great Lakes	15	10
Mideast	8	5
New England	1	1
Plains	28	19
Rocky Mountain	0	0
Southeast	64	44
Southwest	25	17
Total	146	100

RUCCs = Rural-Urban Continuum Codes; BEA = Bureau of Economic Analysis.

Note: This map presents hospital closure data (permanently closed and converted) for nonmetro counties (RUCCs 4–9) between 2005 and 2023. Totals may not sum due to rounding. States in BEA regions: (1) Far West: AK, CA, HI, NV, OR, WA; (2) Great Lakes: IL, IN, MI, OH, WI; (3) Mideast: DC, DE, MD, NJ, NY, PA; (4) New England: CT, MA, ME, NH, RI, VT; (5) Plains: IA, KS, MN, MO, ND, NE, SD; (6) Rocky Mountain: CO, ID, MT, UT, WY; (7) Southeast: AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV; and (8) Southwest: AZ, NM, OK, TX.

Source: USDA, Economic Research Service calculations based on hospital closure data (as of January 11, 2024) from the Cecil G. Sheps Center for Health Services Research, University of North Carolina.

Access to a hospital is needed for residents living in rural areas due to many factors. These include an aging population; higher rates of chronic illnesses due to exposure to agricultural chemicals; high-risk employment in farming, forest, and mining industries; and factors associated with high rates of unemployment, such as stress and depression (Mullner et al., 1989; Henderson & Taylor, 2003). The Government Accountability Office (Government Accountability Office (GAO), 2018) identified rural areas as having a higher percentage of elderly residents and a higher percentage of residents with limitations in activities caused by chronic conditions compared with their urban counterparts. Rural hospitals may also be the largest or only employer in certain rural localities. Therefore, the closing of the only hospital in this type of community can affect the local economy. Studies found that hospital closures in nonmetro counties significantly decreased labor force size (Malone et al., 2022) and led to a decline in health care employment (Alexander & Richards, 2023). In addition to a direct impact through employment, local hospitals have positive indirect or spillover effects on the local economy (Davis, 2022; Doeksen et al., 1997).

Rural hospitals may also face more financial stress compared with their urban counterparts. Pink et al. (2022) showed that rural hospitals reported declining levels of profitability in the 9 years (2011–2019) before the COVID-19 pandemic. Specifically, they found that the proportion of rural hospitals with a negative profit margin was rising, and the median total margin of these facilities was declining at rates ranging from 1.5 to 3.1 percent. Maxwell et al. (2020), using data from the Centers for Medicare and Medicaid Services (CMS), found that metro hospitals in the United States were twice as profitable as nonmetro hospitals in 2018. This trend held true in most parts of the country except for the Northeast. They further found that rural hospitals in the South and Midwest tended to be the least profitable. Maxwell et al. (2020) also documented substantial variation in hospital profitability across States. According to these authors, the States with the lowest median total margins for rural hospitals were New Mexico (-5.8 percent), Mississippi (-4.8 percent), and Virginia (-4.7 percent), while the largest median total margins were in urban hospitals in South Dakota (29.4 percent), Utah (21.2 percent), and Alaska (20.0 percent). These trends may have been reversed temporarily since COVID-19 began. Hospitals and other healthcare providers have received increased financial help from the Federal Government to offset lost revenue and increased expenses related to the pandemic (Pink et al., 2022).

Most rural patients depend on Medicare and Medicaid to pay for their inpatient hospital bills, and these two programs cover only 50 percent of the hospital inpatient costs (Holmes, 2015). Rural areas are known to have less bed occupancy due to the smaller size of the population that each rural hospital serves (Mullner et al., 1989; American Hospital Association (AHA), 2019), causing greater revenue loss for empty beds compared with urban hospitals. Rural areas are also known to have a higher share of uninsured patients compared with urban areas, and most of the rural patients with private insurance are believed to travel to urban areas to receive better care (Holmes, 2015). Despite progress from the Patient Protection and Affordable Care Act (amended as the Affordable Care Act, or ACA), a persistent gap remains in health insurance coverage, with higher rates of people of color uninsured than non-Hispanic Whites across both metropolitan and nonmetropolitan locations (Rural Policy Research Institute (RUPRI), 2022). The financial health of rural hospitals is also impacted by rural hospital bypass behavior (residents choosing more distant facilities for care) (Radcliff et al., 2003; Holmes, 2015). A recent study by the CMS found that over 33 percent of inpatient stays were at a hospital for treatment that might have been rendered by the nearest rural hospital (CMS, 2020). Kaufman et al. (2016a) studied the liquidity or current assets, profitability or revenue generated, staffing, capital structure or total assets, and utilization of rural hospitals and noticed a relationship between higher values for each of these variables and a higher success rate regarding hospital operations. The North Carolina Rural Health Research Program (NC RHRP) routinely tracks rural hospital closures and studies potential predictors. The researchers concluded that profitability is one of the main predictors of rural hospital closures (Maxwell et al., 2020). Based on the Financial Distress Index developed by the NC RHRP, hospitals identified as high risk had closure rates 60 times higher than hospitals identified as low risk between 2006 and 2014 (Kaufman et al., 2016b).

The Federal Government, through various agencies, administers multiple policies and programs that provide financial support for rural hospitals. For example, the Department of Health and Human Services (HHS) administers five[6] Medicare special payment designations for rural hospitals. Through this program, rural hospitals that meet certain criteria receive higher reimbursements for hospital services than they otherwise would receive under Medicare's standard payment methodology (GAO, 2018). HHS also administers rural grants, cooperative agreements and contracts, and other approaches for rural health care delivery and payment. The ACA, enacted in 2010, expanded the Low Volume Hospitals (LVHs) program temporarily (Whitaker et al., 2016). The establishment of the Federal Office of Rural Health Policy (FORHP) in 1987 was partly in response to the number of rural hospital closures (GAO, 2018).

Another Federal program that offers financial support for rural hospitals is the Community Facilities (CF) Program administered by USDA, Rural Development (RD). This program offers grants and loans for rural America to improve facilities and infrastructure, including hospitals, other health facilities and organizations, assisted living facilities, rehabilitation centers, public buildings, schools, community-based facilities, and fire and rescue stations. The program covers costs for land acquisition, professional fees, purchase of equipment, and technical assistance. USDA, RD has obligated $22.5 billion between 2000 and 2020 through the program, with nearly $6 billion of this going to rural hospitals. Despite the funding amount that has been obligated over several decades, only one published study has investigated the impacts of the CF Program on recipient outcomes (Cho & Rupasingha, 2021), and no studies exist on the program's impact on rural hospitals. The objective of the present research is to study the impact of CF funding on rural hospital survival.

[6] The five payment designations are: Critical Access Hospital (CAH), Sole Community Hospital (SCH), or Medicare Dependent Hospital (MDH), Low Volume Hospitals (LVH), and Rural Referral Center (RRC) (GAO, 2018).

Literature

The literature related to rural hospital closures in the United States appears to fall into several strands. While one strand investigates the impacts of closures on economic outcomes, another strand of studies focuses on the impacts on health outcomes. A third strand of studies centers on factors associated with closures. Some studies focus on both impacts of closures and factors associated with closures.

Rural hospitals are often sizable employers in their communities, providing jobs to doctors, nurses, technicians, and administrative staff. They also support the local economy indirectly by buying goods and services from other businesses, such as food, laundry, and construction companies (Malone et al., 2022). However, the economic effects of closing rural hospitals remain unclear, with studies offering conflicting evidence. Holmes et al. (2006) showed that closing the only hospital in a community decreases per capita income and increases local unemployment, but closing hospitals in communities with a nearby alternative hospital had no long-term economic effects. Ona et al. (2007) found no significant differences between rural counties affected by hospital closures and those that did not have closures. Malone et al. (2022) found that rural hospital closures decreased labor force size in a community. Rural hospital closures lead to a decline in healthcare employment but not in other economic metrics (Alexander & Richards, 2023; Chatterjee et al., 2022; Miller et al., 2017).

A recent Government Accountability Office (GAO) study (Cosgrove, 2020) found that rural hospital closures caused patients to travel long distances to get care, as well as reduced the number of doctors in a county, resulting in reduced access to health care services for rural residents. Additionally, rural counties with higher poverty and unemployment rates have shown an increase in age-adjusted death rates for all causes (Bell et al., 2021). Richman and Pink (2017) found that residents in rural high-risk financial distress communities have higher rates of poor health, obesity, and smoking. Gujral and Basu (2019) linked hospital closures in rural areas with increased patient mortality. However, Joynt et al. (2015) found no significant difference in annual mortality rates between patients in hospital service areas with or without closures compared with matched areas without closures.

Many studies that center on factors associated with hospital closures focus on those that affect hospital balance sheets (Harrison, 2007; Holmes, 2015; Kaufman et al., 2016; Topchik et al., 2020; Carrol et al., 2023). These studies demonstrated the relationships between hospital closures and factors such as capital efficiency, Medicaid expansion status in the State, reduced profitability, liquidity, equity, patient volume, staffing, and residents without insurance. Studies also linked unemployment rates, age and case mix of insured people, Government control, and hospital productivity to rural hospital closures (Mullner et al., 1989; Lee & Alexander; 1999; Rhoades et al., 2023).

To the best knowledge of this report's authors, the impact of Federal assistance on U.S. rural hospital closures has not been studied. The present report contributes to literature on that relationship by estimating the impact of a long-standing Federal Government assistance program on the survival of U.S. rural hospitals.

The Community Facilities Program

Under the Community Facilities (CF) Program umbrella, grant and loan programs are offered for rural America to improve facilities and infrastructure, including hospitals, health care clinics, assisted living facilities, rehabilitation centers, public buildings, schools, community-based facilities, and fire and rescue stations.

These programs also cover costs for land acquisition, professional fees, purchase of equipment, and technical assistance (USDA, RD, 2021). Administrative program data were obtained from the Rural Housing Service (RHS), an agency of USDA, RD. The authors used project descriptions and North American Industry Classification System (NAICS) codes to select hospital-related investments (NAICS code 622110) between 2000 and 2020. The CF Program invests in hospitals, including but not limited to the construction of a clinic or hospital, renovation and repair, upgrade of facilities and equipment, and the purchase of medical equipment and beds in rural communities.

Eligible borrowers for the Community Facilities (CF) Program include public bodies, community-based nonprofit corporations, and federally recognized tribes. Eligible areas are rural areas, including cities, villages, townships, and towns, and federally recognized Tribal lands with no more than 20,000 residents based on the latest U.S. Census data. Program funding is available as low-interest direct loans, grants, or a combination of loans and grants, as well as loan guarantees. Loan guarantees may be combined with commercial financing to finance one project if all eligibility and feasibility requirements are met. Priority (based on a point system) is given to communities with a population of 5,500 or less and to low-income communities with a median household income below 80 percent of the State nonmetropolitan median household income.

There are additional requirements for applicants to the program:

- An entity must have the legal authority to borrow money, obtain security, repay loans, and construct, operate, and maintain the proposed facilities.
- Applicants must be unable to finance the project from their own resources and/or through commercial credit at reasonable rates and terms.
- The facilities must serve the rural area where they are or will be located.
- The project must demonstrate substantial community support.
- An environmental review to assess the environmental effects of proposed projects must be completed and acceptable.

The Community Facilities (CF) Program invested $5.7 billion in hospitals between 2000 and 2020, about 25 percent of total CF investments ($22.5 billion).[7] These investments were made in 389 counties (13 percent of all U.S. counties). From all hospital investments, the program invested $4.7 billion in 330 nonmetro counties. Figure 3 shows the trend of CF investments in hospital-related services as a percentage of total CF investments over time. For CF investments in hospitals, 99.8 percent were loan programs (82 percent direct loans and 18 percent guaranteed loans), and 0.2 percent were grants. Table 3 shows how much CF funding has been allocated to each Bureau of Economic Analysis (BEA) region and the amount of those investments that went to hospitals. The Southeast region, which had the most hospital closures since 2005, received 25 percent of total CF hospital obligations. The Plains region received the highest share (33 percent) of total CF hospital investments, followed by the Great Lakes (14 percent) and Rocky Mountain (7 percent) regions. A similar regional breakdown of CF investments was observed (last two columns of table 3) when the CF hospital investments were restricted to nonmetro counties. Figure 4 provides a more disaggregated State-level distribution of CF funding for nonmetro counties (between 2000 and 2020) and rural hospital closure side by side (between 2005 and 2020).

[7] To put these hospital investments into perspective, according to a report by the Center for Healthcare Quality and Payment Reform (CHQPR, 2024), more than 600 rural hospitals were at risk of closing in 2023. CHQPR also concluded that increasing payments to levels sufficient to prevent closures of the at-risk hospitals would cost about $4 billion per year ($6.7 million per at-risk hospital). Given that the CF Program obligated $383 million for 59 hospitals (6.5 million per hospital, nearly meeting the CHQPR estimate) in 2020 (the latest year the data were available), the program was a significant source of finance for rural hospitals.

Table 3

Community Facilities (CF) investments by U.S. Bureau of Economic Analysis region, 2000–20

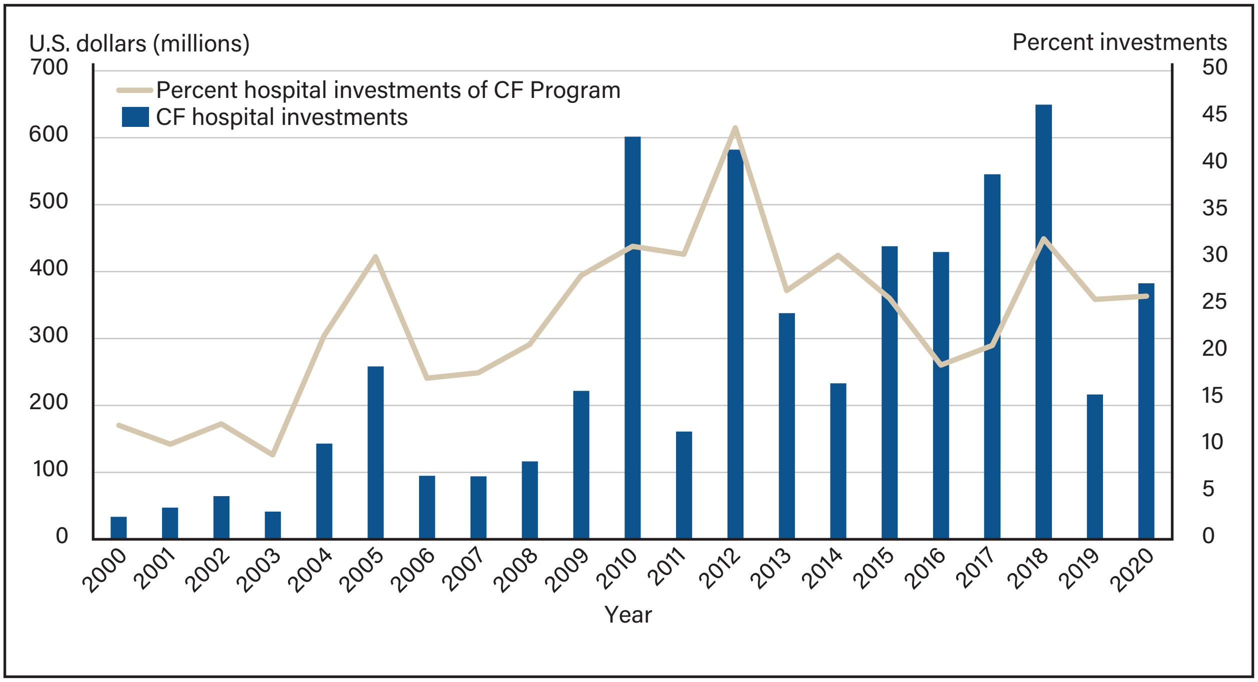
Region	Total CF investments (billion U.S. dollars)	CF hospital investments (billion U.S. dollars)	Percent of total hospital investments	CF hospital investments in nonmetro counties (billion U.S. dollars)	Percent of hospital investments in nonmetro counties
Far West	$2.20	$0.30	5	$0.20	4
Great Lakes	$2.50	$0.80	14	$0.70	15
Mideast	$1.90	$0.30	5	$0.10	2
New England	$1.20	$0.10	2	$0.10	2
Plains	$4.10	$1.90	33	$1.80	38
Rocky Mountain	$1.20	$0.40	7	$0.40	9
Southeast	$7.90	$1.40	25	$1.10	23
Southwest	$1.10	$0.30	5	$0.30	6
U.S. territories	$0.10	$0.0001	0	$0.00	0
Puerto Rico	$0.20	$0.03	1	$0.00	0
Total	$22.50	$5.70	100	$4.70	100

Note: The percent of total hospital investments is the Community Facilities (CF) hospital investment in a particular region as a percent of total CF investment for the Nation. Totals may not sum due to rounding.

Source: USDA, Economic Research Service using USDA, Rural Development program data.

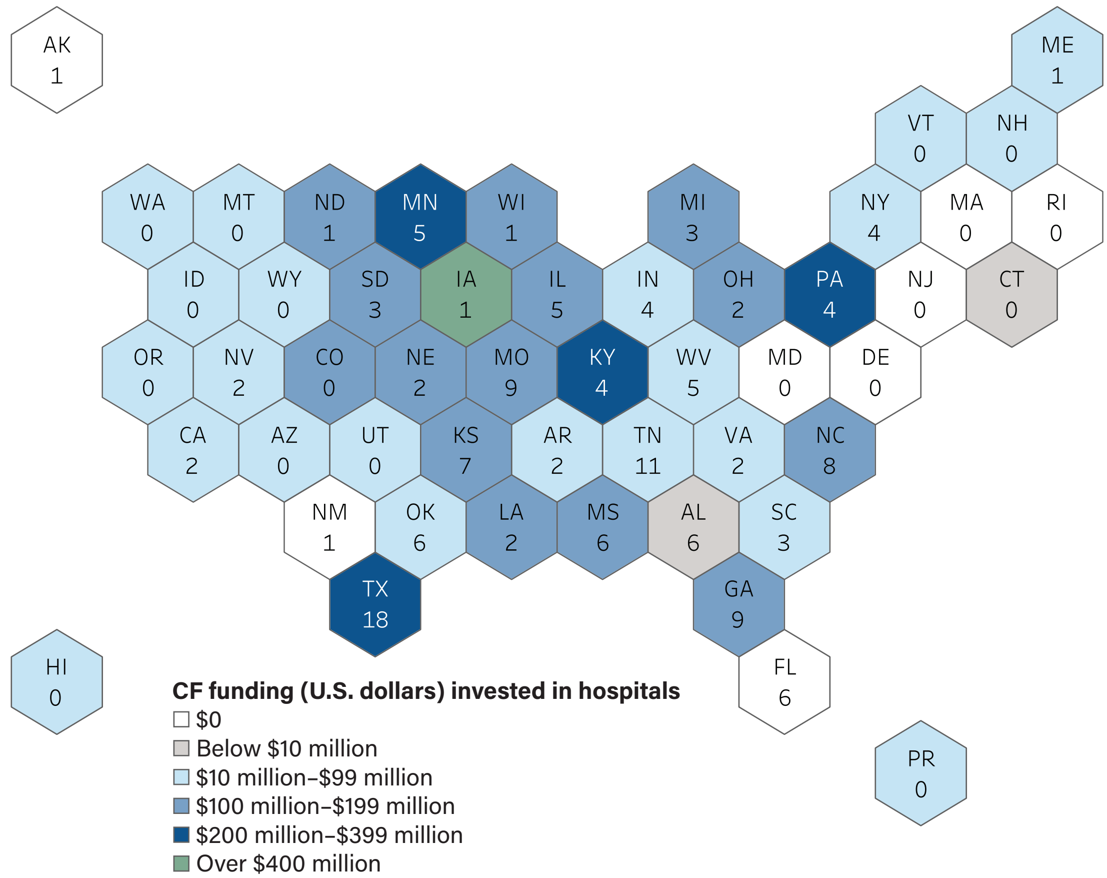
Figure 3

Community Facilities (CF) obligations and the share of their allocation for hospitals, 2000–20



Source: USDA, Economic Research Service calculations using USDA Rural Development program data.

Figure 4
Community Facilities (CF) investment in hospitals (2000–20) and rural hospital closures (2005–23) for nonmetro counties (RUCCs 4–9)



RUCCs = Rural-Urban Continuum Codes.

Note: The map shows a disaggregated State-level (and Puerto Rico (PR)) distribution of Community Facilities (CF) funding (between 2000 and 2020) and rural hospital closures (the numbers in the hexagons) (between 2005 and 2020) for nonmetro counties (RUCCs 4–9).

Source: USDA, Economic Research Service using USDA, Rural Development program data and data from the Cecil G. Sheps Center for Health Services Research, University of North Carolina (accessed January 11, 2024).

Methods

North Carolina Rural Health Research Program defines rural hospital closures as "rural hospitals (including all Critical Access Hospitals) that close their inpatient service or move their services fifteen or more miles away from the current location" (North Carolina Rural Health Research Programs (NC RHRP), 2018, p. 2). Other sources (e.g., Harrison, 2007) include the merger of a rural hospital with other hospitals in this definition. NC RHRP (2018) highlighted several reasons for the difficulty in identifying rural hospital closures accurately: the closing and reopening of some hospitals; geographic moves and mergers; and the closing of inpatient services while retaining some other services. For the survival analysis, the authors of this report defined rural hospital closures as when a hospital record disappeared from the National Establishment Time-Series (NETS) Database (described below). Because of the unique nature of the NETS Database and due to the lack of some of the hospital-related characteristics in this data, this report's authors were not able to designate a hospital as closed if it had moved locations or merged with another hospital and was still active. They were also unable to designate a hospital as closed that had discontinued its inpatient services but retained some of its other services.

Studying the impacts of Federal programs, such as the CF Program, presents considerable estimation challenges. While it is possible to follow CF-recipient hospitals and conjecture whether they survived after receiving a CF grant or loan, such attribution does not indicate whether the recipient hospital's survival is exclusively due to the program. A host of other factors could have affected the survival, and receiving a CF grant or loan itself cannot be considered an exogenous factor. There are missing data issues and program selection biases that need to be addressed in any analysis that studies the impact of these programs on program recipients using observational data. In a parallel universe, researchers should be able to observe what would have happened to the CF-recipient hospitals if they had not received CF funding. More specifically, researchers should be able to estimate the impact of the CF Program on the survival rate of recipient hospitals if they had not received CF funding. But in the real world, this information (counterfactual) is not observable in the data and must be estimated.

The standard practice among researchers for addressing the issue of counterfactual conditions is to observe or estimate missing information using preprogram attributes of program recipients (treated) and nonrecipients (control). For this report's research, the authors built the counterfactual condition using rural hospitals that did not receive CF funding. This approach assumed that the mean outcome observed for the program nonrecipients was the same as the mean outcome that would have been observed for the program recipients if they had not received the program. However, this assumption is often not met, as program recipients and nonrecipients may differ in various characteristics, some of which may affect the outcome of interest, making the outcomes of nonrecipient hospitals invalid estimates of the true counterfactual outcomes. For example, program recipients may be more motivated or have more resources than nonrecipients, which could lead to better outcomes even in the absence of the program. As a result, using program nonrecipients to estimate counterfactual outcomes can lead to an overestimate of the impacts of the program. Another concern in this approach is the possibility that the treated and control groups were on different growth trends before and after the program that affects survival, an issue formally known as nonparallel trends in the outcome variable.

To overcome the differences between treated and control hospitals, the authors used matching techniques to select a control group of hospitals that were similar to the treated hospitals. They used exact matching, as described by Kawabata et al. (2004), on several hospital and community attributes to account for differences in observable characteristics before conducting the survival analysis. This allowed them to modify the control group so that it had a participation likelihood in the program similar to that of the treated hospitals, narrowing the control group to become as similar as possible to the treatment group. To address the issue of nonparallel trends in the outcome variable, the authors included prior (to the program) growth trends of hospitals in the matching exercise. The prior employment size[8] includes the size in the treatment year and 2 years before the treatment. The exact matching required both treated hospitals and their matching control hospitals to be in the same State and same Rural-Urban Continuum Code (RUCC, ranges1–9), to be of the same establishment-type category (stand-alone versus branch/headquarters), the same age group (1–2 years; 3–5 years; 6–10 years; 11 years and older), and the same employment size in the program year and 2 years prior to the program year. The exact matching on State ensured that a treated hospital and its matching hospitals were in the same State, controlling for State-level fixed effects. In a similar manner, exact matching was done on nine RUCCs, adjusting counties for their population size, degree of urbanization, and adjacency

[8] The hospital size was calculated using the number of employees in a hospital. Size variable had 16 size categories from 1 to 16 based on number of employees as follows: 1–49, 50–99, 100–149, 150–199, 200–249, 250–299, 300–349, 350–399, 400–449, 450–499, 500–599, 600–699, 700–799, 800–899, 900–999, and 1,000 and above.

to a metro area. In summary, the authors used exact matching to ensure that the treated hospitals and their matching hospitals were as similar as possible except for the fact that the treated hospitals received CF investments. This helped to isolate the effects of the intervention and to get a more accurate estimate of the impact of CF investments on rural hospital survival. Table 4 presents summary statistics for the variables used in the matching exercise, separately for hospitals that did not receive CF funding (comparison groups) and those that did (treatment group).

Table 4
Descriptive statistics for variables used in matching

	Hospitals with no CF funding		Hospitals with CF funding	
Variable	Mean	Std. dev.	Mean	Std. dev.
Age of hospital at the time of its first CF loan/grant	11.392	7.407	18.518	7.436
Size of hospital at the time of its first CF loan/grant	3.716	4.762	4.167	3.181
Size of hospital 1 year before its first CF loan/grant	3.816	4.837	4.154	3.168
Size of hospital 2 years before its first CF loan/grant	3.928	4.897	4.198	3.186
Whether the hospital is a stand-alone, a branch, or headquarters of a chain (1, 0)	0.562	0.496	0.473	0.500

CF = Community Facilities. Std. dev. = standard deviation. 1 = stand-alone hospitals; 0 = a branch, or the headquarters of a chain.

Note: These numbers were calculated after matching State and Rural-Urban Continuum Codes (RUCCs) and after making sure potential comparison hospitals came from the same State and same county types based on RUCC codes but before matching on age, employment size, and establishment type. The National Establishment Time-Series (NETS) hospital data used for this study do not include several important hospital-level characteristics, such as number of beds, doctors, and financial status.

Source: USDA, Economic Research Service calculations from NETS data.

The research question addressed in this report was whether receiving a CF grant or loan decreases the risk of rural hospital closures. The survival time for a hospital was calculated as the length of time from the CF funding receipt year, either until it ceased to exist or until the end of the sample period. Survival analysis was conducted using the sample of treated and control hospitals in the matched sample.

Data, Data Linking, and Matching

The primary data sources for the statistical analysis were CF Program data from the USDA Rural Housing Service (RHS) and the National Establishment Time-Series (NETS) data from Walls & Associates. The authors used CF project descriptions and North American Industry Classification System (NAICS) codes to identify CF hospital investments. They focused on CF hospital-related grants and loans obligated for the period between 2000 and 2019. The NETS database has longitudinal establishment-level data constructed using business-level data from Dun & Bradstreet's (D&B) Dun's Market Identifier (DMI) files. Walls & Associates compiles annual records of the underlying D&B data into a longitudinal series using the Data Universal Numbering System (DUNS) number. The NETS data cover nearly every U.S. business unit that has operated in the United States since 1990, including sole proprietors, small privately owned firms, farms, nonprofit organizations, and public sector establishments such as post offices and public schools. This research used NETS data from 1990 to 2019, which contained DUNS number and location information, employment, and business start and ending dates in addition to other variables. NAICS code 622110 was used to identify hospitals, and according to the NAICS classification, this industry includes "establishments known and licensed as general medical and surgical hospitals primarily engaged in providing diagnostic and medical treatment (both surgical and nonsurgical) to inpatients with any of a wide variety of medical conditions. These establishments maintain inpatient beds and provide patients with food services that meet their nutritional requirements. These hospitals have physicians and other medical staff to provide patient care services. These establishments usually provide other services, such as outpatient services, anatomical pathology services, diagnostic x-ray services, clinical laboratory services, operating room services for a variety of procedures, and pharmacy services."[9]

The CF Program administrative data contained information such as the DUNS number and the addresses of program recipients, the obligated year, and the amount. For the survival analysis, the authors needed to create a control group of hospitals that were similar to CF-funded hospitals in terms of several characteristics. The survival analysis also required following each CF-funded hospital after it received a CF grant or loan and the facility's selected control hospitals to track their survival. All this information came from the NETS data, so the authors needed to link the CF data with the NETS database. A total of 421 hospitals received at least 1 CF grant or loan between 2000 and 2019. These CF recipient hospitals were linked to NETS hospital data using the unique DUNS number assigned to a hospital, as well as the hospital name and address. Altogether, the authors recorded an 87-percent link rate (366 CF-recipient hospitals). Next, the authors used exact matching techniques to select a control group of hospitals from nonrecipient hospitals that closely matched the hospitals that received CF funding using the covariates described above. This exercise identified 187 exact matching treated hospitals to 7,105 control hospitals from the NETS database. This means that certain treated hospitals have more controls than others. The study used appropriate weights to address this issue (see appendix for details). Matching was done with replacements, meaning that a control hospital can be used more than once as a match so that the average quality of matching will be improved, resulting in a decrease in bias.

Estimation

The authors used the data sample resulting from the matching exercise described above[10] to study the impact of the CF Program on rural hospital survival. While CF investments occur in both metro and nonmetro counties, the main focus of this analysis was on hospital closings in nonmetro counties.[11] The program impact on survival was estimated using the Cox proportional hazards model (Cox, 1972), which has been used extensively in previous studies on the likelihood of business survival. The authors examined the hazard rate (the likelihood that a CF recipient hospital in the sample would close during the following year) in comparison to matched non-CF-recipient hospitals in the sample if the facility had lasted up to a specific point in time (year) after the program. The time from the grant/loan year until a hospital closes, or until the end of the period under consideration, was used to determine the survival duration. The period for the analysis spanned from 2000 to 2019 (the last year in the NETS database). Since the CF Program data spanned this whole time period, an analysis focusing on a 20-year period would subject the early grant/loan recipients to longer time periods and later recipients to shorter time periods. Instead of having longer time series for early cohorts and shorter series for later cohorts, the authors limited the timeframe for computing survival time since the grant/loan receipt year to concentrate on the short- and medium-term effects of the program. This type of event-study technique weighed grant and loan cohorts equally after the CF investment was

[9] Quoted from the NAICS Association's NAICS Code Description web page (accessed March 13, 2024).

[10] Please see the appendix for technical details of the data linking and matching methods.

[11] Estimation results for matched hospitals in all counties are also presented for comparison purposes (table 6).

received. Three time periods[12] were calculated after the first CF grant/loan received: (1) survival of 6 years, (2) 8 years, and (3) 10 years after receiving a CF grant/loan. The variable of interest is whether a hospital received a CF grant/loan.

Several covariates were added in addition to the variable of interest in survival regressions based on earlier studies on business survival (Audretsch & Mahmood, 1994; Christie & Sjoquist, 2012). According to these studies, older and larger enterprises should exist longer. However, other studies reveal declining effects as businesses age and enlarge. The squared term of these variables is typically included in the modeling of this nonlinearity. Previous research found that multiunit firms' learning curves are less steep for their establishments than they are for stand-alone businesses (Audretsch & Mahmood, 1994), and that multiunit firms' establishments have better access to capital. As a result, multiunit firms' establishments may survive longer than standalone businesses. In contrast, several researchers (Reynolds 1988; Christie & Sjoquist, 2012) argued that multiunit enterprises may be more open to closing a single branch and combining resources into other branches than a stand-alone institution. The study data included the age of the hospital prior to receiving CF funding, the number of employees, squared terms of age of the hospital and employee size, and a measurement of whether the hospital was an independent business or part of a multiunit hospital chain. Despite using a matched control group and controlling for several hospital-level observable characteristics, the hazard rates of hospitals could still differ from each other due to unobserved hospital-level differences that could yield inaccurate results (Jenkins, 2005). To take this into account, the authors estimated the survival model using an econometric technique that is robust to unobserved heterogeneity. The appendix to this report provides more detail on the methodology used.

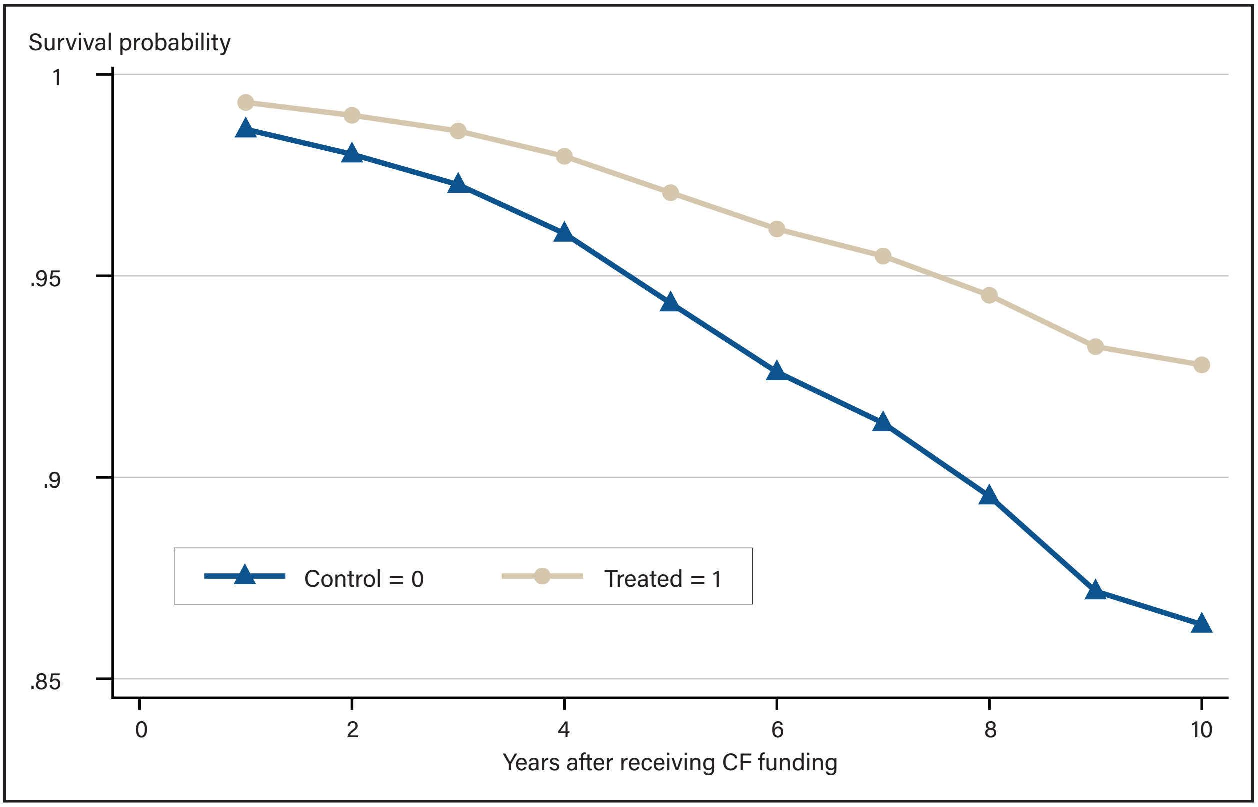
Results

Figure 5 shows the probability of survival for two matched groups of hospitals for nonmetro counties for 10 years after the receipt of CF funding: one group is CF funding recipient hospitals, and the other group is hospitals that did not receive CF funding. This chart is based on the Kaplan-Meier estimator, which can be considered a way of estimating the proportion of hospitals that are still in business after receiving CF funding in comparison to those matched hospitals that did not receive CF funding. The chart helps to visualize how survival probabilities change over time after the first receipt of CF funding for treated hospitals and their matched control hospitals. It shows descriptive evidence that hospitals in the group that did not receive CF funding exit at a faster rate than those in the group that received CF funding. In other words, even though the two groups of hospitals were initially similar, the survival rate of hospitals that received CF funding differed notably from those that did not. The multivariate survival analysis reported next is intended to isolate this effect.

[12] There wasn't enough variation in the exit variable to consider earlier years.

Figure 5

Survival probability over a 10-year period after the Community Facilities (CF) Program for hospitals that did (treated group) and did not (control group) receive funding in nonmetro counties



Source: USDA, Economic Research Service calculations based on National Establishment Time-Series (NETS) data and USDA Rural Housing Service administrative data.

To treat early and late CF recipients equally, the authors restricted the timeframe for computing survival time since the first grant/loan receipt to concentrate on the short- and medium-term effects of the program. Table 5 presents the results of the survival analysis for nonmetro counties and includes three periods that take the CF funding year into consideration: survival of (1) 6 years, (2) 8 years, and (3) 10 years after receiving a CF grant/loan. The statistical tests conducted to select models demonstrated the superiority of the model with unobserved heterogeneity over the model without it. The results presented in table 5 (see appendix table A.1 for technical details) are based on estimates with unobserved heterogeneity.

Table 5

Survival analysis results: Matched hospitals in nonmetro counties

6-year survival	8-year survival	10-year survival
CF Program-recipient hospitals were 94 percent less likely to fail than nonrecipients.	CF Program-recipient hospitals were 90 percent less likely to fail than nonrecipients.	CF Program-recipient hospitals were 88 percent less likely to fail than nonrecipients.

CF = Community Facilities.

Note: These results are drawn from results presented in appendix table A.1. For results reported in the above columns, the report's authors limited the timeframe for computing survival time since the grant/loan receipt year to a number of years after that. For example, 4-year survival represents the 4 years after the first grant/loan.

Source: USDA, Economic Research Service using data from USDA, Rural Development and the National Establishment Time-Series (NETS).

Results presented in column 1 of table 5 show that the recipients of the CF funding had nearly a 94-percent lower failure rate than a group of comparable nonrecipient hospitals 6 years after the loan/grant; 6 years after obtaining CF funding, a hospital's chances of failing are lower than for those hospitals that did not receive CF support. The predicted probability of failure for hospitals receiving CF funding is 0.461 out of 1,000, whereas the predicted probability of failure for hospitals not receiving CF funding is over 5 out of 1,000. This shows that hospital failure risk has decreased in CF-funded hospitals. Over time, there appears to be less of an effect of the CF Program on hospital survival. Eight years after obtaining a CF loan or grant, the program participants had a 90-percent lower failure rate compared with similar nonrecipients. The program participants were 88 percent less likely to fail 10 years after program funding. This implies that, over the course of 10 years, about 0.466 out of 1,000 CF recipients were likely to fail compared with a probability of 2 hospital failures per 1,000 nonrecipients.

Table 6

Survival analysis results: Matched hospitals in all counties

4-year survival	6-year survival	8-year survival	10-year survival
Receipt of CF loan/grant			
CF Program-recipient hospitals were almost 100 percent less likely to fail than nonrecipients.	CF Program-recipient hospitals were 93 percent less likely to fail than nonrecipients.	CF Program-recipient hospitals were 90 percent less likely to fail than nonrecipients.	CF Program-recipient hospitals were 86 percent less likely to fail than nonrecipients.

CF = Community Facilities.

Note: These extracted results are drawn from results presented in appendix table A.2. For results reported in the above columns, the report's authors limited the timeframe for computing survival time since the grant/loan receipt year to a number of years after that. For example, 4-year survival represents the 4 years after the first grant/loan.

Source: USDA, Economic Research Service using data from USDA, Rural Development and the National Establishment Time-Series (NETS).

The authors also estimated the model for survival of hospitals located in all counties in the matched sample, and these results are presented in table 6 (appendix table A.2). Results in column 1 show that the recipients of the CF Program had almost a 100-percent lower failure rate than a group of comparable nonrecipient hospitals 4 years after receiving the loan/grant. The likelihood of a hospital failing 4 years after receiving CF funding is much lower than the likelihood of failure for hospitals that do not receive CF funding. For CF-funded hospitals, the predicted likelihood of failure is 0.001 hospitals out of 1,000, while the predicted likelihood of failure for non-CF-funded hospitals is almost 3 out of 1,000. The impact of the CF Program on hospital survival seems to diminish over time. Six years after receiving a CF loan or grant, recipients were 93 percent less likely to fail than similar nonrecipients. Eight years later, they were 90 percent less likely to fail, and 10 years later, they were 86 percent less likely to fail. This suggests that over the course of 10 years, about 1 out of 1,000 CF-recipient hospitals were likely to fail compared with a probability of 5 hospital failures per 1,000 nonrecipients. These findings demonstrate that the CF Program had a beneficial association with most recipient hospitals' ability to continue operating even 10 years later.

Conclusion

In this study, the authors investigated how effective investments from USDA's Community Facilities (CF) Program were on the viability of program-recipient hospitals in nonmetro counties. In comparison to a reference group of comparable but nonreceiver hospitals, the study found evidence that CF investments appear to help recipient hospitals in nonmetro counties survive longer. This is also true for CF hospital investments made in hospitals located in all counties.

Due to several limitations in the estimation approach and data, these findings should be evaluated with considerable care. One shortcoming in the National Establishment Time-Series (NETS) hospital data used for this study is that several important hospital-level characteristics were missing, including the number of beds and doctors and financial status, which could be essential in creating a control group similar to the hospital group that received program loans or grants. Also, the treated hospitals might have been able to get more money for the same reasons they were able to get financing from the CF Program, even though the study employed exact matching to correct the selection bias in the data. For instance, the CF grantees might be inspired to look for further financial assistance from other sources, such as nonprofits and State and local governments, and they might have been granted it for the same reasons they got CF support. If so, the study cannot assert that receiving CF Program money was the only factor in CF recipients' lower failure risk when compared with matched nonrecipients; the beneficial effect could be due in part to other financial assistance these hospitals received. Future research could investigate the impacts of other Federal or State funding programs or private investments on rural hospital closures. In addition, the matched control hospitals might have received such investments but not the CF Program recipients. In that case, the impacts shown in the study results are underestimated, possibly confounding the results. As the number of matching factors is increased to maximize the effectiveness of matching, there is a concern that exact matching will reduce the treated sample size and sample variability. Since the authors controlled for pretreatment employment size of the hospital when matching, new hospital constructions were automatically excluded from their econometric analysis. The pretreatment employment size of the hospital was matched to bring the treated and control hospitals up to par before the program investments were received. However, if the new hospitals had a stronger (or weaker) survival response to CF funding than existing hospitals, then this exclusion caused a negative (positive) bias in the results. Additionally, the authors were not able to account for rural hospitals that were conversions, which involve a hospital ceasing to offer inpatient services but keeping some services operating. Finally, even though exact matching was used as a technique to create matched control groups, it is important to be aware of its limitations (see appendix for details). Small sample sizes, reduced generalizability, and the possibility of unobserved differences can make exact matching a less than perfect tool in isolating the program impacts on rural hospital survival provided in this report.

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Appendix

Identification

Differentiating a program's true impact from other influencing factors has been a long-running challenge, as evidenced in reviews of the literature on program impacts on expected outcomes. Past trends can significantly affect present results. For instance, the CF Program recipient hospitals might show improved survivability, but that observation could be due to a general upward trend in the growth of treated hospitals (those given Federal Government support), not the program itself. The treated hospitals might inherently perform better than the nontreated comparison hospitals. A program implemented in a thriving group of treated hospitals might seem successful because of external factors (observable and unobservable), not because of the program's own merits.

The ideal scenario to overcome this challenge would be to observe what would have happened to the CF recipient hospitals if they did not receive CF funding. More specifically, it should be possible to estimate the impact of a CF Program on the survival rate of recipient hospitals if they had not received CF funding. However, this is practically impossible because of the difficulty to recreate the past where a treated group of hospitals didn't experience the program. Creating a control group of hospitals that doesn't participate in the program allows for some comparison, but this is never perfect, given that the two groups might inherently differ in ways that influence their survival.

Various statistical methods can help account for some of the observable and unobservable factors and isolate the program's effect, but they all come with limitations. In this report, the authors used matching techniques to select a control group of hospitals that were similar to the treated hospitals. Exact matching, as described by Kawabata et al. (2004), was used on several hospital and community attributes described in the text to account for differences in observable characteristics before conducting the survival analysis.

However, there are some limitations to exact matching. Matching on multiple characteristics can be very strict. This might lead to very small comparison groups, which can make any statistical analysis not very reliable. Even with exact matching of observed characteristics, there might be unobserved factors that differ between the groups. These factors could influence the outcomes and skew the estimated impacts. The matched groups might be very specific due to the exact criteria, and the program's impact observed in this limited group might not apply to the broader population it is intended for.

Data Linking, Methods, and Estimation

The authors linked CF recipient hospitals to National Establishment Time-Series (NETS) data using a combination of exact and fuzzy matching. A total of 421 hospitals received at least one CF grant or loan between 2000 and 2019. First, the authors linked CF recipient hospitals to NETS using the unique DUNS numbers assigned to hospitals. Due to missing DUNS numbers in the CF Program data, this matching resulted in linking about 67 percent (282 hospitals) of CF recipient hospitals to NETS. Next, the authors exact-matched remaining unmatched hospitals using only company names and location ZIP Codes and obtained an additional 60 (14.3 percent) matched hospitals. To link the remaining unlinked hospitals, the authors used a record-linkage method implemented by the Stata program called *reclink*. This procedure was used to match hospitals by their address and company name, allowing for typographical errors or differences in abbreviations.[13] Using this record-linking procedure, the authors were able to link an additional 24 hospitals (6 percent) of the total CF recipients to the hospitals in the NETS database. Altogether, an 87-percent match rate (366 CF-recipient hospitals) was recorded. Next, exact matching techniques were used to select a control group of hospitals from nonrecipient hospitals that closely matched the hospitals that received CF funding in terms of the covariates described in this report. Matching was done with replacement, meaning that a control hospital can be used more than once as a match so that the average quality of matching will be improved, resulting in a decrease in bias. After matching hospitals that received a CF grant or loan to those that did not receive CF funding, 179 CF recipient hospitals[14] had no matching control hospitals, reducing the sample of treated hospitals to 187.[15] The matching exercise identified 7,105 exact-matched control hospitals from the NETS database. This sample of matched treated and control hospitals was used in the survival analysis.

Because exact matching creates a situation where some treated hospitals have more control observations than other treated hospitals, the authors followed a recommendation by Ho et al. (2007) and used the variable-ratio matching method in their survival analysis. This procedure includes all matched controls for each treated hospital and is preferred to other restricted sampling frames, such as one-to-one and one-to-two (or one-to-*n*) matching because it reduces variance without any increase in bias (Ho et al., 2007). Since the number of matched controls for each treated observation varies, this method requires incorporating appropriate weights (Ho et al., 2007; Stuart, 2010). To account for this variability, control observations were given a weight inversely proportional to the number of control hospitals matched to a particular treated hospital (Stuart, 2010). For example, if one treated hospital was matched with only one control hospital, that control received a weight of 1. If another treated hospital was matched with five controls, each of those controls received a weight of one-fifth. Treated hospitals were imputed a weight of 1.

The Cox proportional hazards model (Cox, 1972) has been widely used to estimate the likelihood of establishment survival. The authors extended this framework to estimate the probability of a hospital exit using a discrete-time proportional hazards model. This model is more effective for handling right-censored duration data that are observed in discrete (annual, in the present case) rather than continuous-time data (Cameron & Trivedi, 2005; Jenkins, 1995). Empirically, the authors used a complementary log-log (called cloglog) specification (Jenkins, 1995) to accommodate the underlying discrete time when a survival spell of an establishment ends. Given that t is a year at which a hospital in the data is at risk of exit after receiving CF funding, the probability of an exit at each t provides information on the duration distribution and the discrete-time hazard rate. The specification for the hazard rate is (Jenkins, 1995):

$$h_i(t) = 1 - exp\{-exp[\theta(t) + \beta'X_i]\}$$

where $\theta(t)$ is the baseline hazard modeled using dummy variables to represent each year at risk, and X_{it} is a vector of covariates. Rather than specifying a specific functional form for θ(t), the authors performed a nonparametric estimation of the baseline hazard by including duration-interval-specific dummy variables for each year an establishment is at risk of going out of business.

Despite using a matched control group and controlling for several hospital-level observable characteristics, the hazard rates of hospitals may still differ from each other due to unobserved heterogeneity that can yield

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[13] The fuzzy matched establishments underwent significant manual review to ensure a valid link to the appropriate establishment in the NETS data.

[14] While summary statistics revealed unmatched treated hospitals to be seemingly somewhat younger, larger, and independently operated on average, no noticeable pattern was observed in terms of their locations based on RUCCs.

[15] One unavoidable drawback of exact matching is the tradeoff between the closeness of the match obtained and the number of observations in the sample. The closer the match, the smaller the matched sample size.

inaccurate results (Jenkins, 2005). An estimation without considering unobserved heterogeneity may result in an overestimation of the negative duration dependence or an underestimation of the effect of the explanatory variables on the hazard (Van den Berg, 2001). In the estimation, the authors incorporated unobserved individual heterogeneity in a discrete-time duration framework (Jenkins, 1995) and applied a nonparametric approach to test if unobserved heterogeneity was driving the results. Duration models were estimated in STATA using the cloglog and xtcloglog command (Jenkins, 2005), and xtcloglog assumes normally distributed unobserved heterogeneity. The authors created duration-interval-specific dummy variables, one for each spell year at risk after the receipt of CF funding.

The matched dataset must be reorganized so that, for each hospital, there are as many data rows as there are time intervals at risk of the event (exit) occurring for each hospital. The authors needed to go from the simple dataset (group size), with one row of data per hospital, to another dataset in which each hospital contributed Ti rows, where Ti was the number of time periods (years) i was at risk of the event. In effect, an unbalanced panel data setup was required. The number of observations reported in the results tables in the appendix is based on this panel structure, not the number of hospitals in the matched sample (this is shown as the number of groups). As the period after treatment increased, the number of years considered increased, and so did the number of observations. Hospitals didn't drop out of the sample as the number of years increased, as the event variable indicates the censored nature of the data (1 indicating exit and 0 indicating no exit). The group size stayed the same, but as more hospitals exited each year, the event variable changed from 0 to 1.

Results

Table A.1

Survival analysis for matched hospitals in nonmetro counties

	6-year survival	8-year survival	10-year survival
Community Facilities funding (1, 0)	0.060**	0.095**	0.115**
Hospital age	0.487***	0.456***	0.355***
Age squared	1.020***	1.023***	1.032***
Hospital size	0.517	0.556	0.475
Size squared	1.036	1.031	1.036
Number of observations	11,939	14,259	15,683
Number of groups	2,579	2,579	2,579
Likelihood ratio test	11.56***	13.81***	16.80***

1 = stand-alone hospitals; 0 = a branch, or the headquarters of a chain.

Note: This table presents survival analysis with unobserved heterogeneity for matched hospitals in nonmetro counties. The model was estimated for (1) 6 years after treatment; (2) 8 years after treatment; and (3) 10 years after treatment. There wasn't enough variation in the exit variable to consider earlier years. The likelihood ratio test suggests statistically significant heterogeneity, rejecting the model without unobserved heterogeneity. *** indicates significance of coefficient at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level. Reported values in the table are hazard ratios (exponentiated coefficients): A hazard ratio in the present case explains how often a hospital exits in 1 group of establishments compared with how often it happens in another group of establishments over time. A hazard ratio less (greater) than 1 implies a decrease (increase) in the risk of exit associated with that variable. Reduction in risk is calculated as 1 minus the hazard ratio. A hazard ratio of 1 means that there is no difference between the 2 groups. For example, the first column of results in the table under Community Facilities (CF) funding (1, 0) shows that with CF funding, the risk of failing of recipients over the 6-year period after the program decreased by almost 94 percent (i.e., 1 – 0.060 = 0.94) compared with nonrecipients.

Source: USDA, Economic Research Service calculations based on National Establishment Time-Series (NETS) data and USDA Rural Housing Service administrative data.

Table A.2

Survival analysis for matched hospitals in all counties

	4-year survival	6-year survival	8-year survival	10-year survival
Community Facilities funding (1, 0)	0.002***	0.074**	0.102***	0.166***
Hospital age	0.278***	0.479***	0.419***	0.543***
Age squared	1.034***	1.021***	1.025***	1.018***
Hospital size	0.555	0.556	0.538	0.643
Size squared	1.036	1.036	1.036	1.025
Standalone/branch (1, 0)	0.875	0.693	0.665	0.592
Number of observations	27,167	38,520	46,017	50,010
Number of groups	7,292	7,292	7,292	7,292
Likelihood ratio test	11.08***	14.06***	22.40***	16.80***

1 = stand-alone hospitals; 0 = a branch, or the headquarters of a chain.

Note: This table presents survival analysis with unobserved heterogeneity for matched hospitals in all counties. The model was estimated for (1) 4 years after treatment; (2) 6 years after treatment; (3) 8 years after treatment; and (4) 10 years after treatment. There wasn't enough variation in the exit variable to consider earlier years. The likelihood ratio test suggests statistically significant heterogeneity, rejecting the model without unobserved heterogeneity. *** indicates significance of coefficient at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level. Reported values in the table are hazard ratios (exponentiated coefficients): A hazard ratio in the present case explains how often a hospital exits in 1 group of establishments compared with how often it happens in another group of establishments over time. A hazard ratio less (greater) than 1 implies a decrease (increase) in the risk of exit associated with that variable. Reduction in risk is calculated as 1 minus the hazard ratio. A hazard ratio of 1 means that there is no difference between the 2 groups. For example, the first column of results in the table under Community Facilities (CF) funding (1, 0) shows that with CF funding, the risk of failing of recipients over the 4-year period after the program decreased by almost 100 percent (i.e., 1 – 0.002 = 0.998) compared with nonrecipients.

Source: USDA, Economic Research Service calculations based on National Establishment Time-Series (NETS) data and USDA Rural Housing Service administrative data.