Rural Hospital Closures and Local Economic Decline

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Abstract

This paper studies the local economic impacts of rural hospital closures in the United States. The analysis begins with a difference-in-differences approach using county-by-year panel data on all hospital closures from 2003 through the first half of 2017. The results indicate that closures adversely affect employment, income, labor force participation, establishments, population, rents, and the unemployment rate. Estimated effect sizes grow over time and are explained largely by rural counties that lose their only hospital and in counties where hospitals occupy a large share of the local labor market. While there is little or no evidence of pre-trends, I estimate a range of robustness checks designed to further address endogeneity concerns, such as forward-looking behavior among hospital owners. The results are consistent across these specifications. I also document spillovers, as evidenced by a 1.8 percent decrease in non-hospital employment, an effect that explains 40 percent of the total employment loss. To characterize the significance of the adverse effects, I combine the reduced-form estimates with a spatial equilibrium model of various agents in a local economy. Analysis of the model indicates that rural hospital closures significantly harm welfare, an outcome that is internalized by workers, older residents no longer in the labor force, and landowners.

Keywords: Rural Hospital Closures; Rural Economy; Local Labor Demand Shocks; Spillovers

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1 Introduction

Most of the rural United States has experienced declining economic activity and negative population growth over the last several decades. Given this trend's important implications for economic opportunity and the overall well-being of rural residents, understanding the causes of rural decline is crucial. Research highlights labor sorting and mobility, technological advancements, and higher wages in more populated areas as explanations of this phenomenon.[1] Much less work has analyzed the role of local labor demand shocks in rural areas or their impact on desirable amenities that directly impact residents' quality of life (Autor et al., 2013; Bartik et al., 2019). Considering that rural economies typically support only a small number of firms that generate demand for labor and facilitate consumption of goods and services, these channels appear especially important to understand in explaining rural decline in the U.S.

This paper evaluates how negative local labor demand shocks and amenity losses affect rural communities. Specifically, I estimate the causal impact of rural hospital closures on local labor markets using county-level data on all hospital closures in the U.S. from 2003 through the first half of 2017, together with detailed measures of local economies and populations. Hospitals constitute a unique industry in that they produce both high- and low-skilled jobs and serve as an important amenity to residents and potential migrants. These elements are critical for sustained economic growth. The trend in closures also epitomizes rural economic decline. Figure 1(a) shows the increasing pattern in the number of rural hospitals that have closed since 2003 and it has been suggested that one in five operating facilities are at risk of closing (Mosley and DeBehnke, 2019).

The analysis begins with a difference-in-differences approach that exploits variations in hospital closures over time and space. I document flat pre-trends, consistent with theories that emphasize operating inefficiency, management practices, and government reimbursement rates as the key causes of closure. To further address endogeneity concerns, such as forward-looking behavior on the part of hospital owners, I estimate several variations of the baseline model, including adjusting for industry mix, linear trends, and propensity score re-weighting, as well as models that compare contiguous county-pairs. The results I derive are consistent across these specifications, evidence that any endogeneity bias captured in the estimates is likely small. The estimates then serve as input into a spatial equilibrium model of households and landowners. The framework provides theoretical

[1] See Glaeser et al. (2001), Lee (2010), and Diamond (2016). Research has also documented that employment growth and worker productivity are significantly higher in medium-sized and large metropolitan areas compared with less populated locations (Henderson, 1974; Rappaport, 2018).

guidance for understanding the reduced-form results and aids in estimating the distribution of welfare consequences within a local economy.

In the first set of results, I find that rural hospital closures lead to large and statistically significant reductions across a multitude of economic outcomes. Specifically, closures cause a 4.3 percent reduction in employment and a 2.7 percent reduction in per capita income as well as a 2.8 percent reduction in labor force participation and an 3.1 percent increase in local unemployment rates. Hospital closures also negatively impact population counts and local housing markets, as evidenced by estimated 1.2 percent and 1.3 percent reductions in total population and median rents, respectively. Population reductions occur across all ages, including among individuals 65 years of age and older, a demographic that faces relatively high moving costs and uses hospitals twice as often as younger age groups (Healthcare Cost Utilization Project, 2018).

Three key insights emerge from the reduced-form analysis. First, the impacts of rural hospital closures are sustained with estimated effect sizes that *grow* over time, a finding that underscores the importance of hospitals as a factor in rural economic decline. Second, the effects are largest when a county loses its only hospital and in counties where closing hospitals make up a larger component of local labor markets, evidence that negative shocks to more important industries in rural areas are especially harmful. Third, I find evidence that closures cause significant employment reductions in the non-hospital sector. Specifically, closures lead to a 1.8 percent reduction in non-hospital employment, a decrease in workers that explains 40 percent of the total employment reduction. The spillovers are concentrated in service-providing industries, mainly in counties that lose their sole hospitals and where hospitals compose a substantial share of local employment.

I conclude the analysis by presenting a spatial equilibrium model that builds on the work of Kline and Moretti (2014) and other recent studies (Suárez Serrato and Zidar, 2016; Zou, 2018; Bartik et al., 2019). The goals behind incorporating the model are twofold: the first is to provide a conceptual structure for understanding the effects of rural hospital closures on earnings, prices, amenities, and population size. The second is to characterize local welfare impacts and understand how they are distributed across agents within the local economy. The framework includes many locations, each a small economy, populated by households and landowners. Households are composed of two types: young workers and older residents who are out of the labor force. This setup is similar to spatial models that assume a heterogeneous labor supply comprising high- and low-skilled workers (Diamond, 2016). Those papers, however, do not consider households that are out of the labor force. Consistent with findings from previous studies, older residents face higher moving costs than younger workers do. As a result, the model allows for heterogeneity in amenity and utility changes across household types. Hospital closures are treated as exogenous and impact household utility through changes in earnings, consumption, and amenities. The amenity component is important when considering that rural hospital closures may cause changes in utility that do not occur through changes in income or consumption, such as longer travel times to out-of-county hospitals. Incorporating the reduced-form results and parameter estimates from previous research, analysis of the model shows that rural hospital closures decrease household welfare by 0.5 percent, an effect equal to $1.5 million per county. For landowners in closure counties, welfare is reduced by 2.5 percent, or approximately $37,000 in annual profits. While the welfare reductions I find are significant, the total dollar-denominated loss per closure county is smaller than estimates of hospital operating costs in rural areas. This comparison implies that the cost savings from closure outweigh corresponding local welfare reductions.

This paper contributes to several bodies of literature, including the broad literature that studies how local economies respond to local labor demand shocks.[2] First, this study focuses on hospitals, an industry that has yet to be rigorously examined in the context of local labor market shocks. The setting is particularly unique considering that hospitals not only act as major employers but also contribute in an important way to residents' location preferences and quality of life. Thus, hospital closures affect both local labor demand *and* local labor supply. This is unlike other local labor market shocks, such as manufacturing plant closures, that impact local economies predominately through labor demand. Second, I contribute to the broader literature by focusing on rural communities. Previous work has focused very little attention on the idea that responses to local labor market shocks may vary considerably across place, particularly between urban and rural areas. Given the stark differences in earnings and labor mobility between urban and rural areas, the implications of major labor market adjustments presumably manifest themselves quite differently in urban and rural settings, a conjecture for which I find evidence when analyzing the effects of hospital closures. Unlike closures in rural areas, I document no evidence that urban hospital closures significantly impact local labor markets.

This study also contributes to the literature that has analyzed the relationship between rural hospitals and local economies. First, I improve upon previous work by carrying out a quasi-experimental analysis, making it a priority to address potentially confounding factors, and provide evidence sup-

[2]See Topel (1986), Bartik (1991), Blanchard and Katz (1992), Black et al. (2005), Feyrer et al. (2007), Notowidigdo (2011), Autor et al. (2013), Kline and Moretti (2013), Suárez Serrato and Zidar (2016), and Zou (2018).

porting a causal interpretation of the results. Previous research that has studied the effects of rural hospital closures on local economies generally consist of case studies, where numerous confounding factors exist that can impose bias on the results. Using a rich dataset, this paper is also the first to explore spillover effects caused by rural hospital closures. Previous work that has attempted to quantify the economic contribution of rural hospitals have focused on the aggregate economy. This study goes one step further by estimating effects in sectors of the economy that operate outside of hospitals. Finally, this study provides new insights into the effects of rural hospital closures by incorporating a spatial equilibrium model that helps ground the reduced-form estimates in theory and evaluate the distribution of welfare effects.

The remainder of the paper proceeds as follows: In Section 2 I provide background information on rural hospital closures and review the related literature. In Section 3 I describe the data. In Section 4 I detail the sample construction, describe the identification strategy, and present econometric models used to estimate the effects of rural hospital closures on local economies. In Section 5 I report the main reduced-form results. In Section 6 I discuss robustness and alternative specifications. In Section 7 I analyze spillovers into non-hospital sectors. In Section 8 I present the spatial equilibrium model and welfare analysis and conclude in Section 9.

2 Background and Related Literature

2.1 Rural Hospital Closures in the United States

Nearly 15 percent of hospitals in the U.S. have closed since 1990 and closure rates have increased over the last decade (Carroll, 2019). This trend has generated concern among workers in the healthcare industry and public policy leaders. Beginning in 1989, The Office of the Inspector General (OIG) of the U.S. Department of Health and Human Services published a series of reports on both urban and rural hospital closures within the United States. It was of particular interest to determine the causes and impacts of the closures on local communities, especially in rural areas. The OIG found that 208 rural hospitals closed between 1990 and 2000, approximately 8 percent of all rural hospitals nationally. In response to concerns about rural hospital closures, Medicare created a new program under the Balanced Budget Act of 1997, allowing certain rural facilities to convert to "Critical Access Hospitals" (CAHs) and thereby receive more generous, cost-based reimbursements (U.S. Congress, 1997). The rate of rural closures slowed until more recently, particularly in the years after the Great Recession. The market for hospital operations also has shifted during this time. The trend towards high-tech services, changes in demand, increases in the rate of hospital mergers, and new models of care have all impacted the landscape on which rural hospitals operate.

Factors associated with rural hospital closures have been studied extensively. The literature has highlighted two main predictors of closure. The first is operating efficiency. Several papers have found evidence that inefficient hospitals are more likely to close (Deily et al., 2000; Lindrooth et al., 2003; Ciliberto and Lindrooth, 2007). Inefficiency has been found to be negatively correlated with hospital size and the number of services offered.[3] Indeed, the closed hospitals in my sample feature fewer beds, lower admission rates, and fewer employees than the rural hospitals that do not close (See Table A1). Closures do not, however, disproportionately close in less populated rural areas. The second predictor of closure is cost reimbursement and uncompensated care. Given the considerable fixed costs associated with operating hospitals, their finances are particularly sensitive to care given to the uninsured population. There is much evidence characterizing the relationship between hospital closures, higher rates of uninsured patients, and lower reimbursements from Medicare and Medicaid (Bazzoli and Andes, 1995; Succi et al., 1997; Ciliberto and Lindrooth, 2007).

Recently, a number of papers have highlighted the effects of the Affordable Care Act (ACA) and state decisions to expand Medicaid on hospital sustainability. Lindrooth et al. (2018) found that the ACA Medicaid expansion was associated with improved hospital financial performance and lower likelihoods of closure, especially in rural markets and counties with large numbers of uninsured adults before the Medicaid expansion. Similarly, Duggan et al. (2019) found that the Medicaid expansion in California produced a substantial increase in hospital revenue and profitability, with larger gains for government-operated hospitals.

The COVID-19 pandemic has also placed tremendous strain on hospitals. The AHA estimates \$202.6 billion in losses for America's hospitals and healthcare systems, an average of \$50.7 billion per month, between March through June 2020 (American Hospital Association, 2020). Rural hospitals are especially vulnerable to COVID-19 impacts due to smaller margins, lower occupancy rates, and higher reliance on elective procedures to cover fixed costs. Federal and state relief has been indented to address immediate liquidity needs of hospitals, but this one-time approach does not address long-term sustainability.

[3]See Lindrooth et al. (2003) for a review of this literature.

2.2 Effects of Rural Hospital Closures

Research on the effects of hospital closures has focused largely on how closures impact patient health status. This question is particularly salient in rural communities, where hospital closures create a distance-quality trade-off for patients. While closures increase travel time to healthcare facilities, patient health status may improve if patients affected by a hospital closure receive treatment at higher-quality facilities. The focal point of such work focuses on understanding the relationship between closures and mortality. The evidence pertaining to this relationship is inconclusive. Buchmueller et al. (2006) and Carroll (2019) find that closures increase mortality for individuals who reside in areas near where hospitals close. Other work, such as Joynt et al. (2015), has found no causal relationship between closures and mortality.

Another stream of literature has attempted to estimate the contributions of hospitals to local economies. The majority of such papers are observational case studies that compare outcomes in one or a handful of closure communities with outcomes in control groups. The takeaways from this literature are mixed. Several papers that attempt to quantify the contributions of hospitals to local economies indicate that hospitals are relatively important firms (McDermott et al., 1991; Cordes et al., 1999; Mandich and Dorfman, 2017). Papers that directly investigate the economic consequences of hospital closures also provide evidence of the importance of hospitals to rural economic health. For example, Doeksen et al. (1990) simulated the effect of a hospital closure in rural Oklahoma and estimated that, over a five-year period, approximately 78 jobs and $1.7 million in income would be lost because of the closure.

On the other hand, several papers have reported little or no association between rural economic health and hospital closures. Pearson and Tajalli (2003) examined 24 rural counties in Texas that experienced hospital closures between 1987 and 1989 and found no differences in five economic measures relative to a group of control counties. More recently, Holmes et al. (2006) used closure data from 1990 through 2000 and found that hospital closures do not negatively affect the long-run economic health of local communities. The study reported evidence of negative economic impacts during the year in which a hospital closed, but these effects were not sustained over a longer time period. Finally, Miller et al. (2015) estimated the impact of one hospital closure in rural Illinois on housing values. The study found that the change in value of houses that sold before and after the closure were not affected by the distance from the house to the closed hospital.

3 Data Sources

3.1 Hospital Closures and Characteristics

To construct hospital closure status, I combine information from a number of sources. The primary data come from the American Hospital Association (AHA) Annual Survey Database for the years 2003-2017. The AHA Annual Survey is administered to the universe of hospitals registered by the AHA as operating in the United States and territories. Over 6,000 hospitals are included in the survey, with an annual response rate of approximately 80 percent.[4] The AHA survey database provides detailed information on all types of hospitals in the U.S. and their associated facilities, services, staffing patterns, and reimbursement structures. Most importantly, the data include information pertaining to hospital closures in the U.S. by location and year.

The AHA data, while they are comprehensive, suffer from two limitations that I address here. First, the AHA data does not specify the exact date on which a hospital closes. If a hospital is classified as having closed in survey year t, it is not apparent whether the hospital actually closed in year t or the closure occurred during the final year the hospital responded to the AHA survey, $t-1$. Second, the AHA survey does not specify whether a hospital closed *permanently* or reopened, for example, under a new name. To address these limitations, I hand-checked each of the hospitals that appeared to have closed during the sample period according to the AHA data. Specifically, I used information from online sources such as media articles and state reports as well as data from the Cecil G. Sheps Center.[5] This verification exercise enabled me to obtain exact dates of closure and thereby rule out hospitals that appeared to have closed in the AHA survey but were actually existing facilities that had reopened and reappeared in the AHA under a new identification code.

The Quarterly Census of Employment and Wages (QCEW) serves as my source for county-level annual outcomes in employment, earnings, and number of establishments. The QCEW is based on unemployment insurance records and constitutes a near-census of employment and earnings by sector (e.g. private vs. government) and by industry (e.g. service-providing vs. goods-producing), covering more than 95 percent of all jobs in the United States. In many cases employment and

[4] An institution may be registered by the AHA if it is accredited as a hospital by the Joint Commission on Accreditation of Healthcare Organizations or is certified as a provider of acute services under Title 18 of the Social Security Act. Absent accreditation or certification, an institution licensed as a hospital by an appropriate state agency may still be registered as a hospital by AHA if it meets the requirements listed in Table A2.

[5] The Cecil G. Sheps Center for Health Services Research at the University of North Carolina, has kept a record of rural hospital closures (combining complete closures and hospitals that convert services) since 2005. See https://www.shepscenter.unc.edu/programs-projects/rural-health/rural-hospital-closures/.

earnings data are suppressed to prevent identification of sensitive information from individual industries, so my analysis focuses on published totals of higher-level aggregations that include the suppressed lower-level data.

I use county-level labor force participation and unemployment data from the Local Area Unemployment Statistics (LAUS) published by the Bureau of Labor Statistics (BLS), and county population data from the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute. Population data are available by age, sex, race, and Hispanic origin. Unlike the QCEW, which assigns employment and earnings data to a county based on place of work, SEER also assigns population counts based on place of residence. I also use median rental prices from the U.S. Department of Housing and Urban Development (HUD). I focus on rental prices instead of home values mainly due to data availability. Unlike home values, rental data are available at the county-level for the entire U.S. during each year in my sample and include median rental prices separately for one-, two-, three-, and four-bedroom units. To calculate the aggregate median rental price for each county-year cell, I weight by the proportion of occupied units for each bedroom size using county-level data from the 2000 census.

4 Estimation Methodology

4.1 Sample Construction

The geographic unit of analysis for this study is the county-level, but there is also no consensus on how to classify counties as "rural."[6] The federal government uses two major definitions of rural areas. The first is produced by the U.S. Census Bureau, but this definition does not follow city or county boundaries. The second definition from the Office of Management and Budget (OMB) designates all counties that are not part of a Metropolitan Statistical Area as rural. Both Census Bureau and OMB rural classifications are imperfect. The former defines some suburban areas as rural while the latter includes several rural areas in metropolitan counties. To address these imperfections, this paper borrows its classification standard from Albouy et al. (2018). Specifically, counties are defined as "rural" if (1) more than 50 percent of the population live in a rural area within the county *or* (2) the population density is under 64 per square mile for the entire county

[6]An alternative is to use commuting zones, which respect county borders and may represent a more accurate definition of local labor markets for some areas. Commuting zones, however, are also large enough in many rural places, particularly in the western U.S., where point estimates are likely to decay to the point where I am underpowered to detect existing effects.

(10 acres per person) and the total population of the county is less than 50,000. This definition is particularly useful in that it includes counties that have small urban clusters surrounded by large tracts of sparsely populated land.

After defining rural counties, I use the AHA data to further clean the analysis sample. First, I exclude rural counties that do not have at least one hospital in operation during the beginning of the sample period as these counties make no contribution to the counterfactual outcomes. Second, I focus the analysis on general, short-term acute hospitals and exclude specialty facilities, such as substance abuse treatment centers and psychiatric institutions. I do this to clarify the definition of the treatment and ease interpretation of the estimates. I also exclude hospitals that are operated by larger institutions, including hospitals associated with military bases and prisons. Closures of these hospitals coincide with closures of the parent institutions and including them would certainly add bias to the estimates. Finally, I do not include hospitals that close after the first half of 2017 due to insufficient post-closure outcome data.

Figure A1 illustrates the sample classification, including treatment, control, excluded, and urban counties. The sample consists of 1,830 counties. Table 1 provides summary statistics. There are 97 hospital closures, 58 operating as non-profit hospitals and 39 operating as for-profit hospitals. Of the 97 closures, 41 are the only hospitals in their counties of operation. The remainder of the table provides means and standard deviations of the rural, county-level variables used in the analysis. For closure counties, the statistics are measured during the years prior to hospital closures. For non-closure counties, the statistics are measured in 2003. Closure counties have, on average, more employed individuals and labor force participation. Both hospital and non-hospital employment is also higher in closure counties, but private sector employment is slightly larger in the service-providing and goods-producing sectors in non-closure counties. Per capita income is higher in non-closure counties, but that could reflect a larger population in closure counties. Notably, closure counties have a higher average unemployment rate and fewer establishments. Closure counties are also composed of a larger percentage of non-white and Hispanic residents compared to non-closure counties.

4.2 Identification

The main goal of this paper is to estimate the causal impact of rural hospital closures on local labor markets. In an ideal experiment, hospital closures would be randomly assigned to observably similar rural communities. As conducting such an experiment is not feasible, applying a casual interpretation using a difference-in-differences approach requires outcomes within treatment and control counties to have evolved smoothly in the absence of the closure. This standard "parallel trends" condition must be satisfied in any setting that uses a difference-in-differences design to estimate causal effects.

There are three main threats to the identification strategy. The first I denote as *endogenous trends*. It may be the case that counties where hospital closures occur are experiencing adverse economic conditions that counties without closures avoid. If true, identifying causal effects using a difference-in-differences strategy is complicated by any correlation between the treatment and local economies, potentially leading to biased estimates that capture both the effects of the closure and trends in local economic conditions. Fortunately, evaluating this threat by estimating models that include interactions between treatment status and the years before and after a closure is a straightforward exercise. Such an "event-study" exercise provides both a visual and an empirical test to indicate whether differences in the dynamics of the outcome variables appear between the treatment and controls prior to the occurrence of a closure. Failure to find such differences would provide evidence that hospital closures are orthogonal to determinants of the outcomes, strengthening the causal interpretation of my estimates.[7]

In the absence of pre-trends, a second identification threat is that hospital closures and the outcomes are systematically correlated with unobserved shocks. This is a threat in any quasi-experimental difference-in-differences analysis. For this scenario to be a confounding factor, the unobserved shock(s) would have to occur in the same county and time period as a given hospital closure and not be captured in county-specific demographics or aggregate shocks for which I adjust in the model. As hospital closures are measured using variations across space and time, it is unlikely that this is a threat to casual identification.

I call the third main threat *anticipation bias*. In this scenario, hospitals on the margin of staying open or closing anticipate poor future economic conditions at time $t + n$, where $n > 0$, but choose to close at time t to avoid continued financial distress. Anticipation bias is directly related to the question of why hospitals close, but there is little evidence in the literature that

[7] The instrumental variable approach represents another avenue through which to address potential endogeneity. This approach would be especially challenging to adopt in my setting. To the best of my knowledge, no studies use instruments to identify causal impacts of hospital closures. Although some studies have highlighted Medicare and Medicaid reimbursement rates as important predictors of closures, these variables likely do not satisfy the necessary exclusion restriction. Shift-share instruments (Bartik, 1991) are useful for estimating the effects of changes in hospital employment, but they would not identify all the effects of hospital *closures*.

would indicate hospitals close in response to future economic conditions (Lindrooth et al., 2003). Anecdotal evidence also supports this point. For each hospital in the sample, I searched for reasons cited for closure using media and government reports. Of the 97 hospitals that closed, I found only three cases where hospital management cited the local economy as a reason for closure, and in zero cases were future economic conditions mentioned. Consistent with findings reported in studies discussed in Section 2.1, nearly all hospitals in the sample cited financial distress and poor reimbursement as reasons for closure. Furthermore, it appears that the closed hospitals had forecast horizons that were relatively short, i.e. calculated in days, not years. Services continued to operate as long as possible and, in several cases, some employees were not paid for several weeks prior to when hospitals closed their doors.

4.3 Econometric Models

I begin the formal analysis by estimating event study models designed to test for the presence of confounding pre-trends and capture the evolution of treatment effects over time. The specification takes the following form:

$$y_{ct} = \alpha_c + \delta_{st} + \sum_{k=-5}^{+5} \beta_k I\{t = h_c + k\} + \overline{\beta} I\{t < h_c - 6\} + \underline{\beta} I\{t > h_c + 6\} + \gamma \mathbf{X}_{ct} + \epsilon_{ct}, \quad (1)$$

where y_{ct} represents the outcome of interest in each observation cell indexed by county c and year t. The coefficients of interest are the β_k's on the interaction between the indicator for a hospital closure, h_c, and the indicator function $I\{t = h_c + k\}$, where k indexes time relative to a hospital closure. The effect window includes five years of leads and lags and the endpoints are binned for years outside of this window, represented by $\overline{\beta} I\{t < h_c - 6\}$ and $\underline{\beta} I\{t > h_c + 6\}$.

Included in equation 1 are a full set of county and state-by-year fixed effects, indicated by α_c and δ_{st}, respectively. The county fixed effects adjust for time-invariant variations in county labor market outcomes while the state-by-year effects capture time-varying changes at the state level, such as in aggregate business cycles or public-policy initiatives, that may be correlated with the outcomes. In addition to the fixed effects, the model includes a small number of time-varying demographic covariates, represented by $\mathbf{X}_{ct}$. These include county-specific population percentages in four age groups (1-19, 20-39, 40-64, and 65+ years), two racial groups (white, non-white), the percentage of population that is male, and the percentage of population that is Hispanic. The covariates are intended to reduce standard errors and offer additional controls for any time-varying differences between treatment and control counties. Standard errors are clustered at the county level to account for within-county correlations.

I then estimate a pooled difference-in-differences model that effectively averages the year-specific effects estimated in equation 1. The model is specified as follows:

$$y_{ct} = \alpha_c + \delta_{st} + \beta Closure_{ct} + \gamma \mathbf{X}_{ct} + \epsilon_{ct}. \tag{2}$$

The indicator variable $Closure_{ct}$ takes the value one if county c experiences a hospital closure in year t (and all subsequent years) and zero otherwise. The primary coefficient of interest, β, represents the causal effect of a hospital closure on outcome y.

5 The Effects of Rural Hospital Closures on Local Economies

5.1 Local Labor Markets

I begin the analysis of local labor markets by assessing pre-trends and treatment-effect dynamics using the event study model shown by equation 1. Figure 2 illustrates the results. The outcomes at event-time t are measured relative to the conditions that were in place the year before the hospital closes ($t = -1$), conditional on including county fixed effects, state-by-year fixed effects, and covariates in the model specification.

The results of the event study analysis are striking. In Figures 2(a) and 2(b), the reported findings for log employment and log per capita income show point estimates that are near zero and flat in the years prior to hospital closures. This pattern suggests that the empirical model is adequately adjusting for changes in local economies that may be correlated with hospital closures. The figures show no evidence that hospital closures occurred disproportionately in rural counties suffering from worse economic trends, strengthening credibility that my identification strategy is capturing causal effects. Moving to the post-closure period, we see that in both figures there is an obvious break in the flat pre-trend and a notable reduction in the magnitudes of the estimates. There is an immediate decrease in employment and per capita income by approximately 2 percent. The effects do not diminish with time. Rather, the effect sizes *grow* over time, suggesting that, on average, rural local labor markets do not revert back to pre-closure conditions. The long-run effect sizes following hospital closures ("+6 and later") are approximately twice as large as the estimated effects during the year of the closure.

Figure 2(c) shows that rural hospital closures cause an immediate increase in the unemployment rate. The effect begins to fall back to the pre-closure average within two years but the long-run unemployment rate remains about 0.2 percentage percent higher in counties that experienced a hospital closure. This pattern is dissimilar to that documented in the analysis of Blanchard and Katz (1992) and Feyrer et al. (2007), who suggest that unemployment rates recover from negative local labor demand shocks relatively quickly as a result of population and labor force adjustments. Rather, the sustained response found here implies that population and labor-force adjustments are not large enough to fully alleviate the increases in unemployment rates. One possible explanation for this is that hospital closures lead to employment responses in other sectors of local economies that do not occur immediately after closures.

Turning to log labor force participation, as shown in Figure 2(d), the results mirror the findings for employment and per capita earnings. The pattern exhibits flat pre-trends with immediate and sustained reductions following hospital closures. The effects for total establishments reported in Figure 2(e) are near zero until three years after closures occur, when the number of establishments begins to fall. Quantitatively, the long-run reduction corresponds to there being more than 2 percent fewer establishments in counties with hospital closures, a pattern that is consistent with long-run responses for employment, income, labor force participation, and the unemployment rate.

In Table 2 I report the pooled difference-in-differences estimates derived from equation 2. As seen in column (1), I find that hospital closures reduce total employment by 4.4 percent relative to what occurs in control counties. Adding time-varying controls to the model changes the estimate only slightly. When compared with the average employment level prior to closure, the estimates imply a reduction in employment of between 450 and 461 workers. On average, the closed hospitals in the sample account for 1.7 percent of total county employment. The estimated employment effect is 2.6 percentage points greater than the percentage of workers employed by the closed hospitals. This comparison suggests that the aggregate employment effects are not fully accounted for by hospital employment, evidence that the impacts of hospital closures spill over to other industries. I explore spillover effects directly in Section 7.

The results for per capita earnings are shown in columns (3) and (4). Hospital closures lead to a reduction in per capita earnings of between 2.6 and 2.9 percent, with and without controls. Like those for employment, the earnings estimates are statistically significant at the 1 percent level. In columns (5) and (6), I find that hospital closures are associated with a marginally significant 0.2-percentage-point increase in the county unemployment rate. This effect translates to an approximately 2.7 percent increase, or 30 more unemployed individuals.[8] The estimated reduction in labor force participation shown in columns (7) and (8) is between 2.9 and 2.8 percent, equating to between 432 and 447 fewer individuals in the labor force. The estimated unemployment rate and labor force participation responses largely explain the total employment effect. While rural hospital closures directly cause some individuals to transition from employment to unemployment, over 90 percent of the estimated employment reductions come through labor force participation adjustments in closure counties. In the final two columns I find negative but insignificant reductions in total establishments. The 95 percent confidence interval does not rule out a more than 2 percent reduction, but the large standard errors limit statistical precision.

5.2 Population and Rents

Figure 3 plots results for population and median rental responses. The total population effect is shown in Figure 3(a). The pre-closure estimates are flat and near zero, evidence that counties where hospital closures occur are not also experiencing disproportionate changes in local population counts. During the post-closure period, there is an immediate 0.5 percent reduction in population that gradually grows over time, similar to the estimated employment, labor force participation, and total establishment responses. The long-run effects corresponds to a 2 percent population reduction in rural closure counties. To further investigate the negative population effect of hospital closures, I estimate population responses across several age groups. The results are shown in Figure 3(b), Figure 3(c), and Figure 3(d). The dis-aggregated effects indicate that population reductions are distributed across all ages.

The results reported in the first four columns of Table 3 quantify the event study findings for population. The point estimates reported in column (1) imply that hospital closures reduce total county populations by 1.2 percent relative to what occurs in control counties. The estimate is significant at the 95 percent level and corresponds to a reduction of approximately 397 people. In columns (2) through (4) I report population estimates by age group. The results for each group are similar in magnitude to the total population estimate, with the largest reduction in percentage terms corresponding to adults 65 and older.[9]

The event study plot for median rental prices is shown in Figure 3(e). The pattern shows

[8] I also used data from the Regional Economic Information System to estimate unemployment insurance spending. The results are positive but not statistically significant (coefficient= 0.012, s.e.= 0.014).

[9] I also examined total payments of retirement and disability benefits data from the Regional Economic Information System. I find a negative but statistically insignificant decrease of 0.7 percent.

rents fall slightly during the first five years after a closure but, later, converge back to pre-closure levels. The pre-trends, however, are noisy, which limits a causal interpretation. The point estimate reported in column (5) in Table 3 implies rural hospital closures lead to a 1.3 percent decrease in median rental prices. This percentage reduction corresponds to a modest \$8.33 decrease relative to the mean rent prior to closure.

5.3 Heterogeneity

I next investigate heterogeneous treatment effects in two ways. First, I separate closure counties by whether they lose their sole hospitals. Previous research has suggested that local economic and population effects may be most responsive when a community loses it only hospital (Holmes et al., 2006), although other studies have failed to reach the same conclusions (Stensland et al., 2002). Adverse effects on local firm production and employment are likely to be more pronounced in counties that lose their only hospitals because hospitals themselves act as major purchasers of local goods and services. Additionally, residents may be discouraged from locating in a county that lacks a hospital, further impairing future economic growth. The results for main local labor market, population, and housing outcomes are shown in Table A3. I find that the effects are considerably larger in rural counties that lose their sole hospital. Estimated employment and per capita income reductions exceed 7 and 5 percent, respectively. Similarly, decreases in labor force participation, total establishments, population, and median rents are also much larger relative to counties with at least one other operating hospital.

I also explore heterogeneity sorted by the importance of a hospital to local economies. I expect to find larger effects in counties where closing hospitals make up a greater component of the local labor market. To perform this exercise, I first calculate the median share of employment that the closing hospitals contribute to total county employment. This calculation yields a value of 2.19 percent. I then divided closure counties by whether the percentage of total county employment in hospitals lies above or below this value. As Table A4 shows, I find that adverse effects are considerably larger in counties where hospitals that close make up a larger share of the local economy. The estimates for counties with above-median hospital employment explain the entire aggregate county response.

6 Robustness and Alternative Specifications

In Appendix B, I detail results from a range of robustness checks and alternative specifications. I summarize the results here. First, I decompose the baseline difference-in-differences model into five groups of 2x2 estimators following Goodman-Bacon (2018). Results appear in Table B1. Approximately 94 percent of the baseline estimate is explained by comparisons between rural counties where no hospitals close and rural treatment counties. This finding is consistent with the fact that estimates derived from the difference-in-differences model closely resemble the results from the event study specification, which is comparably more robust to problems pertaining to variations in the treatment status across time.

I next show results derived from several alternative specifications, including models that control for a rich set of county-industry characteristics (Table B2), balanced-panel fixed-effects models (Table B3), and specifications that include county-population weights (Table B4) and county-specific trends (Table B5). To improve balance between closure and non-closure counties, I also estimate difference-in-differences models in combination with propensity-score reweighting using the iterative procedure in Imbens and Rubin (2015) to estimate propensity scores (Table B6). The estimates obtained across all these specifications closely resemble the results obtained from the baseline specification.

Given that neighboring counties are presumably more similar to one another, I then estimate a county border-pair specification following Dube et al. (2010) and Borgschulte and Cho (2019). Results are shown in Table B7. I also re-estimate the baseline specification that *excludes* border counties from the control group, as spillovers to these counties (if positive) may dilute the true effect of hospital closures on the local economy (Table B8). The estimates obtained from both specifications are largely consistent with the baseline results, suggesting that the degree of bias from including or excluding border counties is small. In the final alternative specification, I estimate the effects of hospital closures in urban counties. Results estimated using the baseline specification (Table B9) and propensity-score reweighting (Table B10) are near-zero and largely not statistically significant. Unlike rural hospital closures, it appears that closures in urban areas do not create meaningful impacts on local labor markets.

7 Spillover Effects on Non-Hospital Industries

The results reported so far provide suggestive evidence that rural hospital closures lead to substantial employment reductions over and above what can be explained by hospital employment. In this section, I return to the analysis of spillovers and estimate direct effects of hospital closures on non-hospital economic sectors. I first estimate employment and establishment spillovers of hospital closures using hospital-level data from the AHA annual survey.[10] The AHA data are particularly useful for this analysis because they allow hospital employment, payroll, and establishments to be subtracted from the QCEW data. Formally, I define the outcomes for county c in year t as follows:

$$log(Net\ Employment_{ct}) = log(Employment_{ct} - Hospital\ Employment_{ct}), \tag{3}$$

$$log(Net\ Establishments_{ct} = log(Establishments_{ct} - Hospitals_{ct}). \tag{4}$$

Defining net employment and establishments is straightforward, as shown by equations 3 and 4. I simply take the difference between total county employment and establishments in year t with hospital employment and total hospitals, respectively. The regression specifications are the same as presented in Section 4. I also deconstruct the non-hospital sector into private service-providing and goods-producing (manufacturing, construction, and natural resources) industries.[11] Hospitals are considered service-providing establishments, so estimating effects for private goods-producing industries is straightforward using the QCEW. For private service-providing firms, I follow the same approach outlined above to net-out employment and establishment contributions of private hospitals.

In Table 4 I report the results. In columns (1) and (2), I show that hospital closures lead to a 1.8 percent reduction in non-hospital employment, a decrease in workers that explains approximately 40 percent of the total employment loss. Non-hospital establishments are reduced by .07 percent, consistent with the non-hospital employment effect, but are not statistically significantly different

[10] I do not report estimated spillover impacts on earnings because (1) payroll expenses reported in the AHA are missing for a large share of rural hospitals and (2) the QCEW public-use file suppresses nearly all hospital earnings data for the counties in my sample.

[11] An alternative approach is to follow Black et al. (2005) and divide the economy between "tradable" industries, whose products are nationally or internationally traded, and "non-tradable" industries, whose products are traded mainly locally. This approach is complicated by data suppression in the QCEW public-use file for many specific industry types.

from zero. Importantly, I find no evidence of confounding pre-trends prior to closure, as illustrated by Figure 4. Furthermore, the event study figures provide compelling evidence that the spillovers are indeed caused by hospital closures and that the closures themselves are not driven by trends in other local economic sectors. Results for the private service-providing sector appear in columns (3) and (4). The point estimates are slightly larger across each outcome compared to the total non-hospital results, most notably the 2.5 percent reduction in employment. I find no significant effects of hospital closures on employment and total establishments in the goods-producing sector, as shown in columns (5) and (6). The main takeaway of this analysis is that adverse employment spillovers are entirely concentrated in the service sector, a finding that is to be expected given that, on average, the number of individuals employed in the private service-providing sector is nearly twice as large as employment in the goods-producing sector.

I further explore spillovers by performing the same heterogeneity exercises presented in Section 5.3. The results appear in the Appendix. I first examine the non-hospital sector in its entirety. The heterogeneity estimates appear in Table A5 and follow the same pattern as seen in aggregate local economies. I find statistically significant reductions in non-hospital employment in counties that lose their sole hospital, in counties where hospitals compose a higher share of employment, and in counties that lose a non-profit hospital. I also perform the heterogeneity exercise for private service-providing and goods-producing sectors. The results are shown in Tables A6 and A7. Consistent with the above mentioned findings, the heterogeneous effects are concentrated in service-providing industries.

8 Evaluating Welfare Impacts of Rural Hospital Closures Using A Spatial Equilibrium Model

This section presents a dynamic spatial equilibrium model that follows the framework of Kline and Moretti (2014). The model includes many locations, indexed by c, each a small economy that is populated by households and landowners.[12] While many workers in rural areas own their residences, differentiating between households and landowners allows welfare changes to occur through separate

[12] It is straightforward to extend the framework to allow for a firm-specific component. However, I abstract away from doing so due to data availability and to simplify the model. For example, while I can assume that local firms may earn positive economic profits, I lack estimates on changes in local prices, outside of rents, that are necessary to include as inputs in the firm profit maximization problem. As an alternative, I can model firms as operating in a perfectly competitive market, which is a strong assumption and implies firms bear zero welfare incidence. Doing so, however, has no impact on the magnitude or precision of the welfare impacts for households or landowners.

channels, namely (1) changes in labor income and amenities and (2) changes in landowner profits. Hospital closures are assumed to be exogenous and impact household utility through changes in earnings and amenities. In every time period t, households derive utility from consuming goods and housing, and exhibit heterogeneous preferences over locations. Heterogeneity in preferences is a feature that differs this model from the canonical Rosen-Roback framework (Rosen, 1979; Roback, 1982). The Rosen-Roback model, with homogeneous preferences, perfectly mobile workers, and an inelastic housing supply, predicts that the entire incidence of local labor demand shocks will be capitalized into land rents. By taking a less restrictive stance and including household mobility frictions, the model in this paper allows some of the welfare incidence of local labor demand shocks to fall on inframarginal households.

I divide households into two types: young workers who inelastically supply a single unit of labor in each time period, and older residents who are out of the labor force. Both types of households have access to the same housing market and local amenities. The key difference is that workers and older residents have different location preferences and moving costs. Specifically, I assume that older residents have more severe mobility frictions than younger workers do. This assumption is consistent with research findings that document the fact that retirees in rural areas face higher moving costs and place a higher value on local social networks than younger workers do (Chen and Rosenthal, 2008; Glasgow and Brown, 2012). Importantly, differences between location preferences and moving costs give rise to heterogeneity in terms of willingness-to-pay (WTP) for local amenities and the incidence of welfare changes associated with local hospital closures.

8.1 Household Problem

The local economy is populated by two types of households: young workers, indexed by i, and older residents, indexed by o, who are out of the labor force. The total number of households is denoted by N_{ct}. In each time period, workers inelastically supply one unit of labor.[13] Both workers and older residents have heterogeneous preferences for locations and are free to reside and work in any location. For both types, the problem is to maximize utility in each time period t, defined in

[13]For simplicity, the model does not allow for household transitions between workers and older residents.

Cobb-Douglas form, subject to their budget constraint. Formally:

$$\begin{aligned} max\ u_{ict} &= \alpha ln h_{ict} + \beta ln X_{ict} + \eta ln A_{ict} + \epsilon_{ict} \\ s.t.\ w_{ct} &= r_{ct} h_{ict} + p_{ct} X_{ict}, \end{aligned}$$

$$\begin{aligned} max\ u_{oct} &= \alpha ln h_{oct} + \beta ln X_{oct} + \zeta ln A_{oct} + \epsilon_{oct} \\ s.t.\ w_{c} &= r_{ct} h_{oct} + p_{ct} X_{oct}. \end{aligned}$$

The variables h_{ict} and h_{oct} represent the amount of housing consumed by each type at cost r_{ct}, while X_{ict} and X_{oct} denote the amount of a numéraire good sold on the global market that is consumed at price p_{ct} normalized to 1. The variables α and β denote the shares of income spent on housing and goods, respectively. Unlike workers, incomes are assumed to be constant for older residents across each time period.[14]

The A_{ict} and A_{oct} terms represent local amenities, including hospitals, that are available to workers and older residents, respectively. The amenity component is important when considering that hospital closures likely induce changes in utility that do not appear in income measures or changes in consumption. Finally, ϵ_{ic} and ϵ_{oc} represent idiosyncratic location preferences. To ease the model's tractability, preferences are assumed to be independently and identically distributed $(i.i.d)$ according to a Type-I Extreme Value distribution with scale parameter s and mean zero. Larger values of ϵ_{ic} and ϵ_{oc} imply that workers and older residents have stronger preferences for residing in a given location owing, for example, to the desire to live close to family members or highly valued local amenities.

Solving the maximization problem for both workers and older residents yields expressions for their indirect utility:

$$\begin{aligned} v_{ict} &= a + ln w_{ct} + \eta ln A_{ct} - \alpha ln r_{ct} + \epsilon_{ict}, && (5) \\ &= u^{i}_{ct} + \epsilon_{ict}, && (6) \end{aligned}$$

[14]In the model, older residents are out of the labor market, so I assume their fixed income comes from government insurance programs like social security and Medicare.

$$v_{oct} = a + lnw_c + \zeta lnA_{ct} - \alpha lnr_{ct} + \epsilon_{oct}, \tag{7}$$

$$= u^o_{ct} + \epsilon_{oct}, \tag{8}$$

where a is a constant equal to $\alpha(ln\alpha - ln\lambda) + \beta(ln\beta - ln\lambda)$.[15] Households choose to live in location c at time t if it maximizes their indirect utility, which depends on real income, local amenities, and individual location preferences. The $i.i.d$ Type-I Extreme Value assumption for ϵ_{ict} and ϵ_{oct} implies that the total population of each type can be specified as a function of individual preferences, i.e.

$$N^i_{ct} = \frac{e^{u^i_{ct}/s_i}}{\sum_{c'} e^{u^i_{ct}/s_i}},$$

$$N^o_{ct} = \frac{e^{u^o_{ct}/s_o}}{\sum_{c'} e^{u^o_{ct}/s_o}}.$$

Taking logs on both sides yields

$$lnN^i_{ct} = \frac{1}{s_i}u^i_{ct} - \frac{1}{s_i}a_{ct}, \tag{9}$$

$$lnN^o_{ct} = \frac{1}{s_o}u^o_{ct} - \frac{1}{s_o}a_{ct}, \tag{10}$$

where the total population of each type depends on real income and amenities, a constant, and scale parameter s, which represents moving costs and governs the strength of idiosyncratic preferences for location c.[16] Intuitively, if s is large, households are more inelastic to local labor shocks. In the extreme case where $s = 0$, workers are perfectly mobile (Roback, 1982). A key assumption of the model is that s is larger for older residents than for workers, i.e. $s_o > s_i$.

8.2 Housing Market

8.2.1 Housing Supply

Housing is supplied competitively at marginal cost, is upward sloping, and varies across locations. Land is assumed to be fixed, so the price of housing increases with the total population. This gives

[15] The derivation details are presented in Appendix C.

[16] Note that $a^i_{ct} = ln(\sum_{c'} e^{u^i_{ct}/s_i})$ and $a^o_{ct} = ln(\sum_{c'} e^{u^o_{ct}/s_o})$

way to the following housing supply function:

$$H_{ct}^{S} = k_c r_{ct}^{\theta_c}, \tag{11}$$

where H^S denotes the total housing supply and r_c is the price of housing. The k_c term is a location-specific productivity factor that is assumed to be exogenous and constant over time. Local housing supply elasticity is denoted by $\theta_c > 0$ and governs the strength of housing supply responses to changes in productivity and prices. Housing supply elasticity is exogenously determined according to location-specific factors, such as geography and local land regulations. Outside of the fixed land supply, there are relatively few barriers to supplying new housing in rural areas. Therefore, θ_c is non-zero and small.

Landowners' profits depend negatively on housing supply elasticity, and are a function of the price of housing and occupied housing units, H_{ct}, i.e.

$$\pi_{ct} = \frac{\theta_c}{1+\theta_c} H_{ct} r_{ct}. \tag{12}$$

8.2.2 Housing Demand

Total spending on housing in each location is given by $N_{ct}\alpha w_{tc}$, where N_{ct} and w_{ct} denote the total population and income of workers and older residents, respectively. Let $\frac{1}{\psi_c^H}$ denote the exogenous shift in housing demand caused by a hospital closure, where $\psi_c^H \geq 1$. Local housing demand from households is given by

$$H_{ct}^{D} = \frac{N_{ct}\alpha w_{ct}}{r_{ct}\psi_c^H}. \tag{13}$$

It is straightforward to see that housing demand increases with population and the expenditure share of income spent on housing, while it decreases when local housing costs are higher. When $\psi_c^H > 1$, housing demand decreases in response to a hospital closure. Likewise, $\psi_c^H = 1$ in locations that do not experience a hospital closure.

8.2.3 Housing Market Equilibrium

The local housing market equilibrium is determined by setting the housing supply in equation 11 equal to housing demand in equation 13. After taking the logs on each side, the equilibrium housing price is given by the following equation:

$$lnr_{ct} = \frac{1}{1+\theta_c} lnN_{ct} + \frac{1}{1+\theta_c} lnw_{ct} - \frac{1}{1+\theta_c} ln\psi_c^H + \frac{1}{1+\theta_c} a_H, \tag{14}$$

where $a_H = ln\alpha - lnk_c$. Intuitively, housing prices increase when the local population is larger, income is higher, the share of income spent on housing is higher, and when the productivity of the housing supply is lower. Local housing prices decrease when a local hospital closes. The strength of these relationships depends on the housing supply elasticity. Large values of θ_c imply that the housing supply is more elastic, corresponding to more modest changes in local housing values in response to changes in, for example, population or income. For small values of θ_c, local housing prices will move proportionally to changes in population and income.

8.3 Equilibrium and Welfare Conditions

After substitution and differentiating, the local equilibrium can be characterized using equations 9, 10, and 14:

(1) Local Labor Supply

$$s_i \Delta lnN_{ct}^i = \Delta lnw_{ct} + \eta \Delta A_{ct} - \alpha \Delta lnr_{ct} \tag{15}$$

(2) Older Resident Population

$$s_o \Delta lnN_{ct}^o = \zeta \Delta A_{ct} - \alpha \Delta lnr_{ct} \tag{16}$$

(3) Housing Market Equilibrium

$$\Delta lnr_{ct} = \frac{1}{1+\theta_c} \Delta lnN_{ct} + \frac{1}{1+\theta_c} \Delta lnw_{ct} - \frac{1}{1+\theta_c} \Delta ln\psi_c^H \tag{17}$$

Households: Figure C1 illustrates the welfare effect of a local hospital closure for households. The x- and y-axes represent the marginal preferences and utility of households who live in location c, respectively. The upward-sloping solid red line shows that the utility of living in location c increases with ϵ_{ct}. Similarly, the solid blue line slopes downward because the taste for location c' decreases from left to right. The equilibrium utility is equal to u_{ct}^* with the preferences of the marginal household denoted by ϵ^*_{ct}. When a hospital closes in location c, household utility shifts down to the red dashed line by an amount equal to the change in real income and amenities. The new equilibrium utility level is denoted by u^{**}_{ct}. The population in location c drops, as households with preferences between ϵ^*_{ct} and ϵ^{**}_{ct} move away. The change in household welfare is shown by the shaded purple area. This area is approximately equal to the change in population in location c multiplied by the change in utility, i.e. $(1-\frac{1}{2}\Delta lnN_{ct})\times\Delta u_{ct}$. The total household welfare change is equal to the sum of the welfare changes for workers and older residents, weighted by the respective population shares:

$$\Delta V^H = \underbrace{\frac{N^i_{ct}}{N_{ct}}(1-\frac{1}{2}\Delta lnN^i_{ct})\times\Delta u^i_{ct}}_{\text{Weighted change for workers}} + \underbrace{\frac{N^o_{ct}}{N_{ct}}(1-\frac{1}{2}\Delta lnN^o_{ct})\times\Delta u^o_{ct}}_{\text{Weighted change for older residents}} \tag{18}$$

Recall that $u^i_{ct} = a + lnw_{ct} + \eta lnA_{ct} - \alpha lnr_{ct}$ and $u^o_{ct} = a + lnw_c + \zeta lnA_{ct} - \alpha lnr_{ct}$. Differentiating and substituting these expressions into equation 18 for Δu^i_{ct} and Δu^o_{ct} yields

$$\begin{aligned}\Delta V^H =& \frac{N^i_{ct}}{N_{ct}}(1-\frac{1}{2}\Delta lnN^i_{ct})\times[\Delta lnw_{ct} + \eta\Delta lnA_{ct} - \alpha\Delta lnr_{ct}]\\ &+ \frac{N^o_{ct}}{N_{ct}}(1-\frac{1}{2}\Delta lnN^o_{ct})\times[\zeta\Delta lnA_{ct} - \alpha\Delta lnr_{ct}].\end{aligned}$$

Landowners: The change in welfare for landowners is equal to the change in profits, denoted by

$$\Delta V^L = \Delta lnr_{ct} + \Delta lnH_{ct}. \tag{19}$$

8.4 Amenity and Welfare Estimates of Rural Hospital Closures

Decomposing equation 18 shows that, to estimate the total welfare change for workers, I must first estimate the effects of rural hospital closures on local amenities. Differentiating and rearranging equations 15 and 16 provides equations for the full set of amenity changes associated with a local hospital closure for workers and older residents:

$$\eta ln\Delta A_{ct} = s_i\Delta lnN^i_{ct} + \alpha\Delta lnr_{ct} - \Delta lnw_{ct} \tag{20}$$

$$\zeta ln\Delta A_{ct} = s_o\Delta lnN^o_{ct} + \alpha\Delta lnr_{ct} \tag{21}$$

These equations imply that the change in amenities, expressed as a percentage of income, is equal to the difference between the percentage change in the population, adjusted for the magnitude of location preferences and moving costs, and the percentage change in real income. The intuition behind this result reflects the fact that, in spatial equilibrium, the marginal household must be indifferent to relocating, which means that local prices will respond to changes in local income. The strength of this response will depend on both the elasticity of the local housing supply and individual preferences.

To estimate equations 20 and 21, I combine the empirical results for population (ΔlnN^i_{ct} and ΔlnN^o_{ct}), income (Δlnw_{ct}), and rental prices (Δlnr_{ct}), with parameter estimates drawn from previous research. I assume β=0.65, the share of household wage and salary income spent on locally produced goods, following Bartik et al. (2019) and set α=0.268, the share of income spent on housing, using estimates from The Bureau of Labor Statistics.[17] The labor share of income, y, is set to 0.71 following Albouy et al. (2018). The key parameter difference between workers and older residents resides in the idiosyncratic location preferences and moving costs, where $s_o > s_i$. To capture this heterogeneity, I set s_i=0.3 and s_o=0.6 following Diamond (2016) and Bartik et al. (2019).[18] Putting everything together, the estimated changes in amenities are as follows:

$$\eta ln\Delta A_{ct} = (0.3 \times -0.012) + (0.268 \times -0.020) - (-0.026) = 0.017 \quad (0.005)$$

$$\zeta ln\Delta A_{ct} = (0.6 \times -0.015) + (0.268 \times -0.020) = -0.014 \quad (0.007)$$

The estimates suggest that rural hospital closures impact local amenities differently by household type. Notably, for older residents, higher values of location preferences and moving costs imply that population adjustments are less responsive to changes in real income. As a result, amenities fall following a rural hospital closure. With the amenity estimates in hand, I can now calculate the welfare changes associated with rural hospital closures for households and landowners using equations 18 and 19. The reduced form estimates and parameter values discussed above again are used as inputs into the calculations. I do not observe changes occupied housing units for landowners, so I proxy for changes in this variable by assuming that the change in occupied units

[17] See https://www.bls.gov/opub/ted/2016/urban-and-rural-household-spending-in-2015.htm

[18] Specifically, s_i is equal to the population-share weighted average of the idiosyncratic location preferences/moving costs for non-college educated and college-educated workers estimated by Diamond (2016).

moves in proportion with the change in population. The estimated welfare effects for each household type and for landowners are as follows:

$$\Delta V_i^H = \underbrace{-0.004 \quad (0.002)}_{\text{Welfare change for workers}}$$

$$\Delta V_o^H = \underbrace{-0.009 \quad (0.004)}_{\text{Welfare change for older residents}}$$

$$\Delta V^L = \underbrace{-0.013 \quad (0.006)}_{\text{Change in rental price}} + \underbrace{-0.012 \quad (0.005)}_{\text{Change in occupied units}} = 0.025 \quad (0.011)$$

I estimate the welfare change for workers, older residents, and landowners following a rural hospital closure to be -0.4 percent, -0.9 percent, and -2.5 percent, respectively. All three estimates are statistically significant at the 5 percent level, with standard errors shown in parentheses. After weighting by the associated population shares for workers (0.79) and older residents (0.21), the total household welfare effect is:

$$\Delta V^H = \underbrace{-0.003 \quad (0.001)}_{\text{Weighted change for workers}} + \underbrace{-0.002 \quad (0.001)}_{\text{Weighted change for older residents}} = -0.005 \quad (0.002)$$

I estimate the total household welfare reduction to be -0.5 percent. In terms of average income, the welfare response represents about -$62 per household, or approximately -$1.5 million per county. For landowners, the estimate represents a $37,000 reduction in aggregate profits when weighted by share of income spent on housing. The results in Table A8 show the qualitative patterns of the amenity and welfare estimates do not change when using alternative values of the location preference parameter.

The welfare estimates that I derive above are useful to consider when discussing whether rural hospital closures are an efficient consequence of an evolving market or if interventions intended to keep hospitals open, such as monetary bailouts, are economically justified. Carroll (2019) reports that annual operating costs for rural hospitals prior to closure is approximately $5 million. This number is over three times the total welfare loss I find per closure county and implies that the cost savings from closure outweighs local welfare reductions. It is important to note, however, that the welfare estimates do not account for all losses associated with rural hospitals, most notably increases in mortality. Furthermore, the closing hospitals studied in this paper are generally smaller in size than rural hospitals that remain in operation, implying that the estimate welfare losses may be interpreted as a lower bound for what rural communities can expect as larger hospitals close in the future.

9 Conclusions

This paper evaluates the causal impacts of rural hospital closures on local labor markets. The results show that rural hospital closures adversely impact local employment, per capita income, labor force participation, establishments, population, and housing and rental prices. The impacts are not transitory and are explained by reference to rural counties that lose their sole hospital and in counties where hospitals compose a higher share of local labor markets. The analysis also shows that rural hospital closures lead to spillovers in other sectors of the economy, including a 1.8 percent decrease in non-hospital employment, an effect that explains 40 percent of the total employment loss. To ground the estimates in theory and characterize the welfare impacts created by hospital closures, I develop a spatial equilibrium model of various agents in a local economy. Analysis of the model shows that rural hospital closures reduce welfare significantly for households and landowners, but the size of these reductions are smaller than estimated operating costs.

While this paper makes a number of important contributions to the literature, it is subject to limitations that may provide guidance for future work. First, more work is needed to understand how spillover impacts in non-hospital industries are explained by changes in demand from hospitals that close as opposed to diffusion effects that spread throughout the economy. Analyzing spillovers by industry type using more detailed local-level data is one possible way to investigate this question more carefully. Second, the extent to which spillovers caused by rural hospital closures may be dispersed across space remains unclear. For example, closures may create spillovers into neighboring counties. These spillovers may be positive, if the neighboring counties absorb employment losses from counties that experience a closure, or negative, if a closing hospital was also a contributing industry to the neighboring local economy. Understanding the diffusion of spillovers and their relationship to the distribution of nearby hospitals would represent an interesting next step in this literature.

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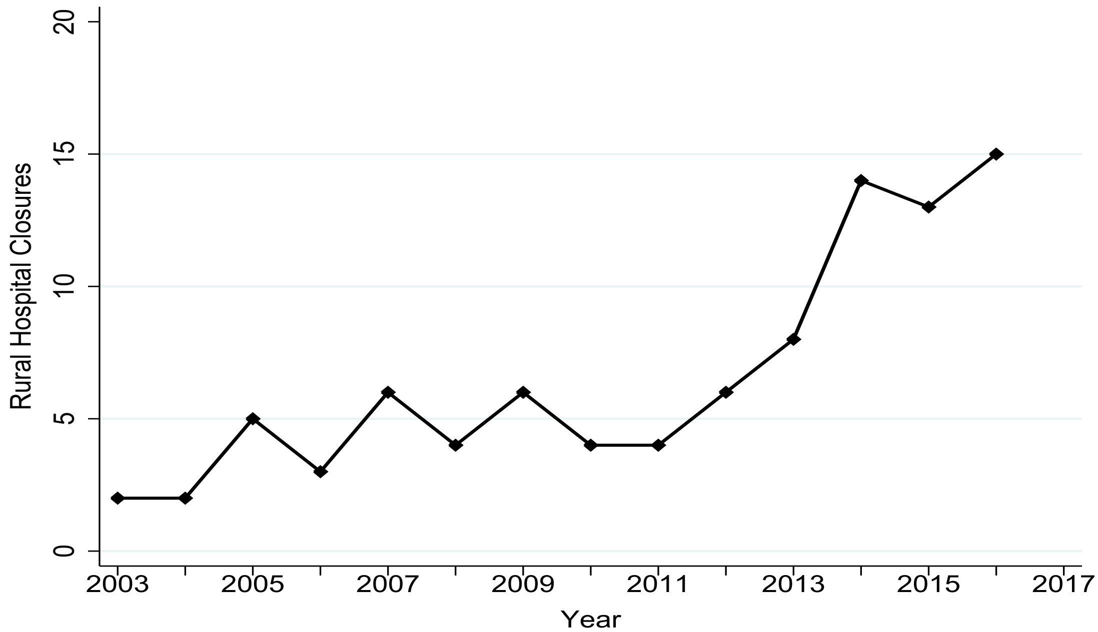
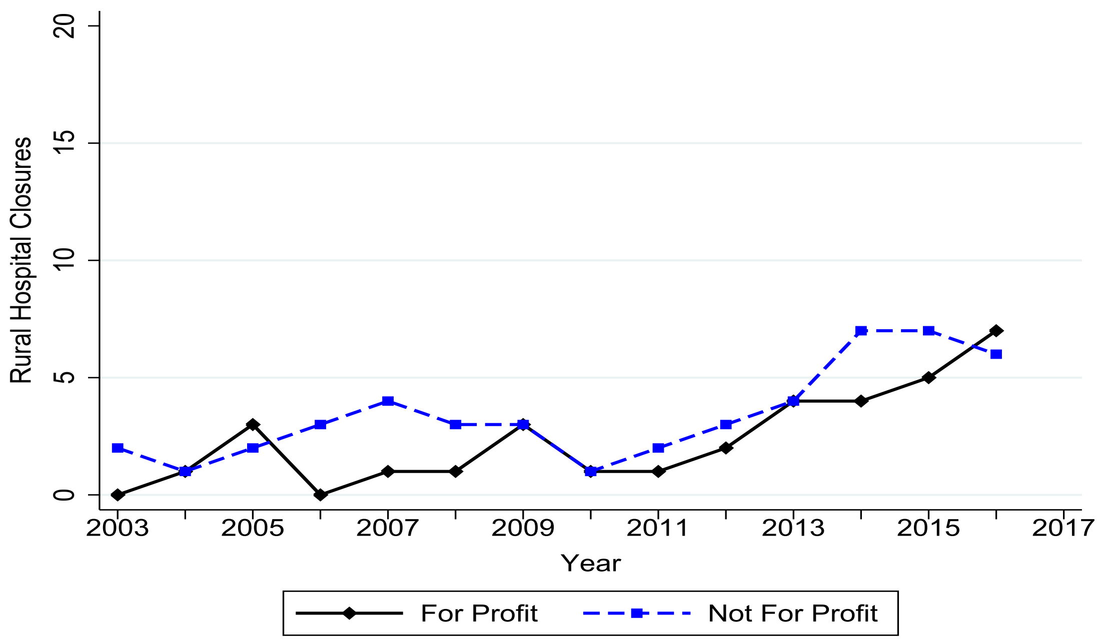
Figure 1: Trend in Rural Hospital Closures

(a) Total Closures



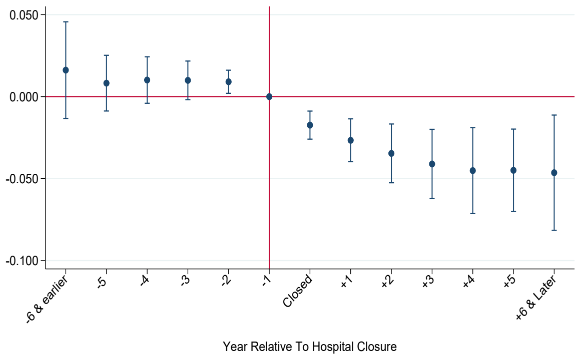
(b) Closures By Ownership



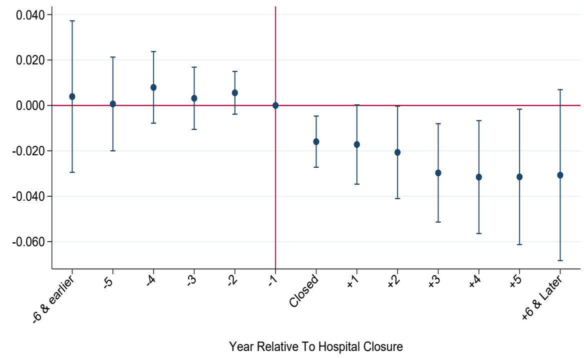
Notes: The above figure shows (a) the trend in rural hospital closures and (b) the trend in closures by ownership from 2003 through 2016. Data analyzed in the paper also includes hospital closures that occurred in the first half of 2017. Data are collected from the AHA Annual Survey of Hospitals.

Figure 2: Local Economic Effects of Rural Hospital Closures

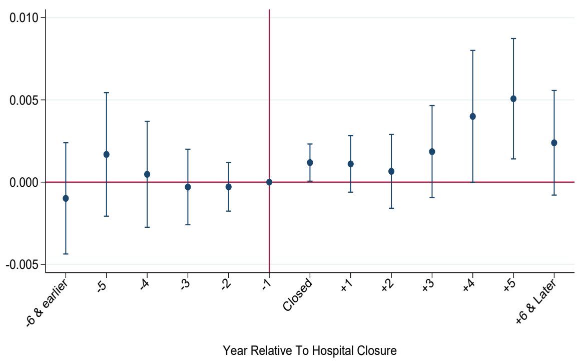
(a) Log Employment



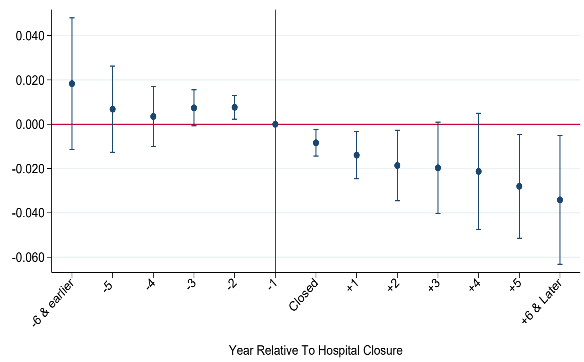
(b) Log Per Capita Income



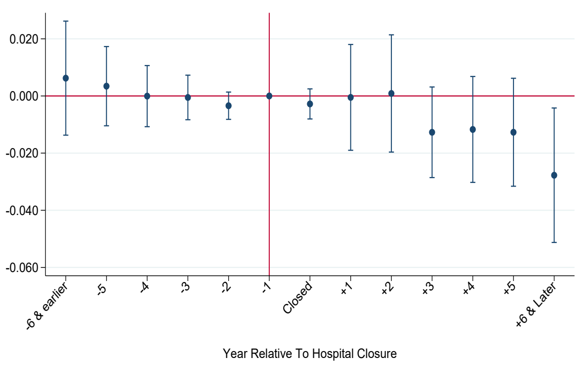
(c) Unemployed Rate



(d) Log Labor Force Participation



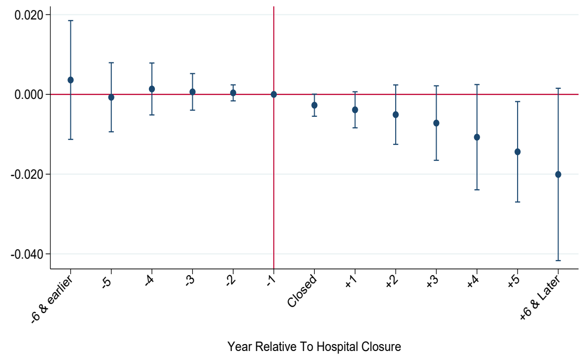
(e) Log Total Establishments



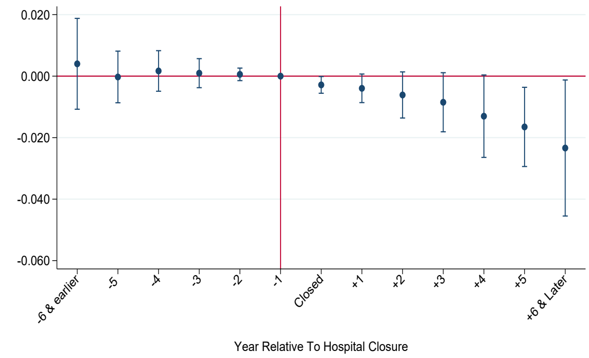
Notes: The above figures show event study plots of county-level economic effects of rural hospital closures. The sample includes rural counties for 2003-2017. The longest vertical line indicates the end of the year before a hospital closure. Bands indicate 95 percent confidence intervals. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level.

Figure 3: Population and Rental Market Effects of Rural Hospital Closures

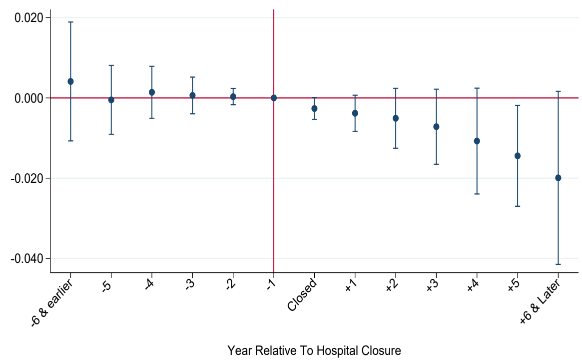
(a) Log Total Population



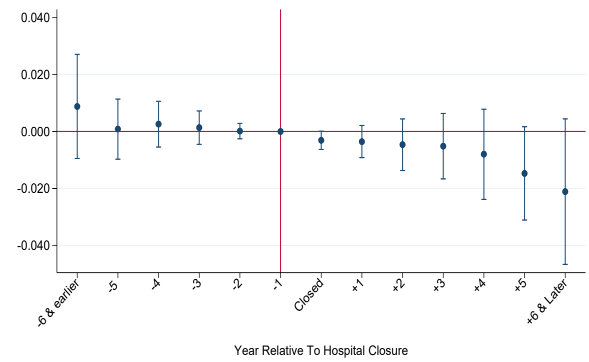
(b) Log 0-19 Population



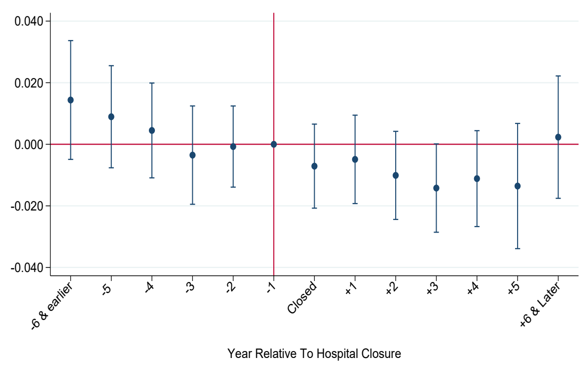
(c) Log 20-64 Population



(d) Log 65+ Population



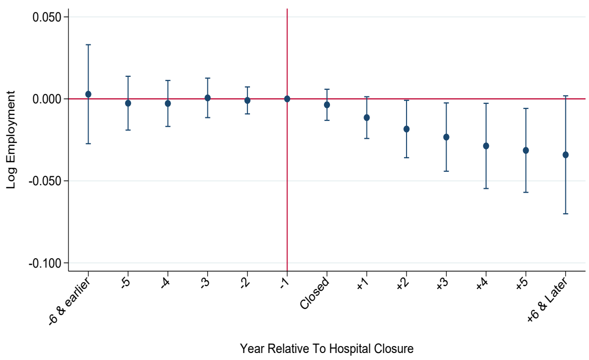
(e) Log Median Rental Price



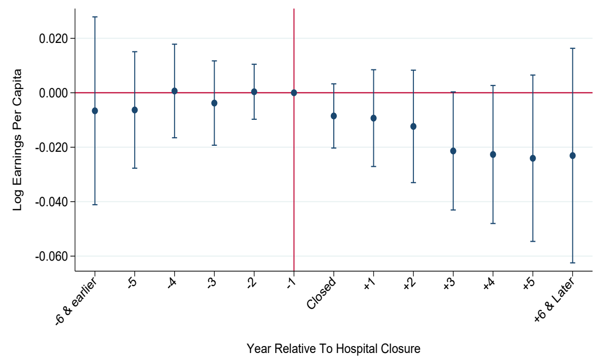
Notes: The above figures show event study plots of county-level population and rental market effects of rural hospital closures. The sample includes rural counties for 2003-2017. The longest vertical line indicates the end of the year before a hospital closure. Bands indicate 95 percent confidence intervals. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level.

Figure 4: Local Economic Effects of Rural Hospital Closures on the Non-Hospital Sector

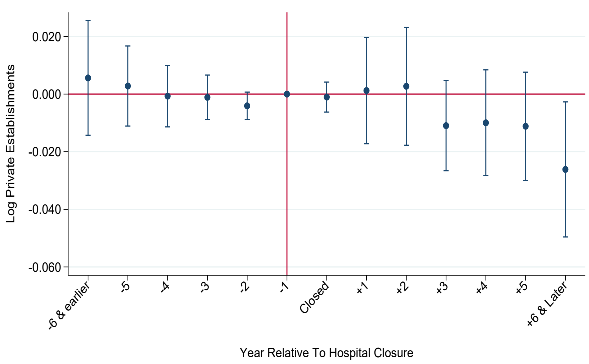
(a) Log Employment



(b) Log Per Capita Income



(c) Log Establishments



Notes: The above figures show event study plots of county-level non-hospital economic effects of rural hospital closures. The sample includes rural counties for 2003-2017. The longest vertical line indicates the end of the year before a hospital closure. Bands indicate 95 percent confidence intervals. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level.

Table 1: Descriptive Statistics

Variables	**Closure Counties** *Mean (SD)*	**Non-Closure Counties** *Mean (SD)*
Total Hospitals and Closures		
Operating Hospitals	1.57 (0.74)	1.20 (0.54)
Total Hospital Closures	97	0
Non-Profit Closures	58	0
For-Profit Closures	39	0
Only Hospital in County	41	0
Economic and Housing Variables		
Total Employment	10,472.67 (9,483.52)	10,439.52 (10,842.94)
Per Capita Income ($2017)	10,679.82 (4,590.08)	11,677.92 (5,077.56)
Unemployment Rate	7.52 (3.28)	6.06 (1.98)
Labor Force Participation	15,421.28 (13,269.57)	15,181.48 (15,761.97)
Total Establishments	768.57 (677.91)	772.22 (778.97)
Median Rent ($2017)	641.36 (149.67)	616.16 (136.28)
Hospital Employment	422.92 (577.30)	372.85 (420.79)
Non-Hospital Employment	10,093.72 (9,150.44)	10,072.89 (10,534.78)
Non-Hospital Establishments	767.03 (677.62)	771.03 (778.76)
Private Service-Providing Employment	5,381.62 (5,444.48)	5,389.44 (6,401.071)
Private Service-Providing Establishments	551.59 (516.62)	549.70 (591.41)
Private Goods-Producing Employment	2,543.09 (2,333.50)	2,653.28 (2,951.69)
Private Goods-Producing Establishments	155.87 (136.44)	163.25 (169.92)
Population and Demographic Variables		
Total Population	33,108.68 (26,485.36)	31,065.19 (30,948.59)
Ages 0-19	8,353.64 (6,764.73)	8,243.02 (8,362.01)
Ages 20-64	19,328.89 (15,822.29)	18,009.84 (18,345.45)
Ages 65 +	5,020.51 (3,927.74)	4,422.22 (4,373.43.34)
% Male	50.37 (2.87)	49.75 (1.91)
% White	81.90 (18.43)	89.37 (15.54)
% Hispanic	8.08 (12.52)	6.27 (11.71)

Notes: The above table presents means and standard deviations among closure and non-closure counties. For closure counties, the statistics are measured during the years prior to hospital closure. For non-closure counties, the statistics are measured in 2003. Hospital data are collected from the AHA Annual Survey of Hospitals. Employment, income, and establishment data are gathered from the Quarterly Census of Earnings and Wages. Labor force participation and unemployment rate data comes from the Local Area Unemployment Statistics program through the Bureau of Labor Statistics. Median rents are gathered from the Department of Housing and Urban Development Office of Policy Development and Research. Finally, population and demographic comes from the Surveillance, Epidemiology, and End Results Program through the National Cancer Institute.

Table 2: County Income and Employment Effects of Rural Hospital Closures

	Log Employment		*Log Per Capita Income*		*Unemployment Rate*		*Log Labor Force*		*Log Total Establishments*	
	Baseline	*Controls*	*Baseline*	*Controls*	*Baseline*	*Controls*	*Baseline*	*Controls*	*Baseline*	*Controls*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hospital Closure	-0.044***	-0.043***	-0.029***	-0.026***	0.002*	0.002*	-0.029***	-0.028***	-0.011	-0.010
	(0.010)	(0.010)	(0.011)	(0.010)	(0.001)	(0.001)	(0.011)	(0.010)	(0.009)	(0.008)
Mean Dependent Variable	10,473		10,680		0.075		15,421		769	
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1830	1829	1829	1829	1830	1829	1830	1829	1830	1829
Observations	27444	27429	27429	27429	27448	27433	27448	27433	27448	27433

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table 3: County Population and Housing Effects of Rural Hospital Closures

	Log Total Population	*Log 0-19 Population*	*Log 20-64 Population*	*Log 65 + Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)
Hospital Closure	-0.012**	-0.013***	-0.012**	-0.015**	-0.013**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.011)
Mean Dependent Variable	33,109	8,354	19,329	5,021	641
Controls	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1819
Observations	27435	27435	27435	27435	26968

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

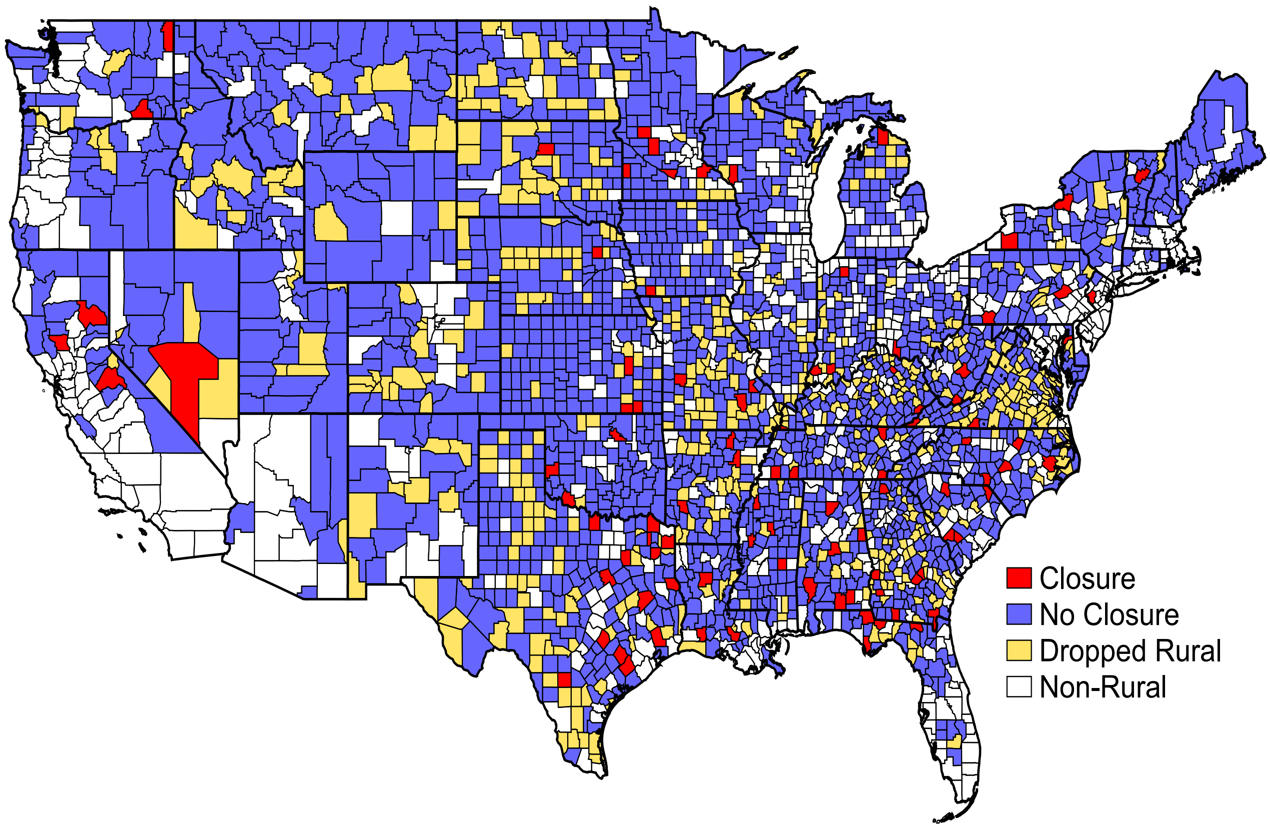
Table 4: Effects of Rural Hospital Closures on the Non-Hospital Sector

	Log Employment	*Log Total Estabs*	*Log Employment*	*Log Total Estabs*	*Log Employment*	*Log Total Estabs*
	(1)	(2)	(3)	(4)	(5)	(6)
	All Non-Hospital		**Private Service**		**Private Goods**	
Hospital Closure	-0.018**	-0.007	-0.025**	-0.009	-0.004	0.002
	(0.009)	(0.008)	(0.011)	(0.010)	(0.020)	(0.011)
Mean Dependent Variable	10,094	767	4,686	552	2,543	156
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829
Observations	27416	27433	27361	27431	27320	27425

Notes: This table shows estimated impacts of rural hospital closures on the non-hospital, private service-providing, and private goods-producing sectors using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Appendix A: Additional Tables and Figures

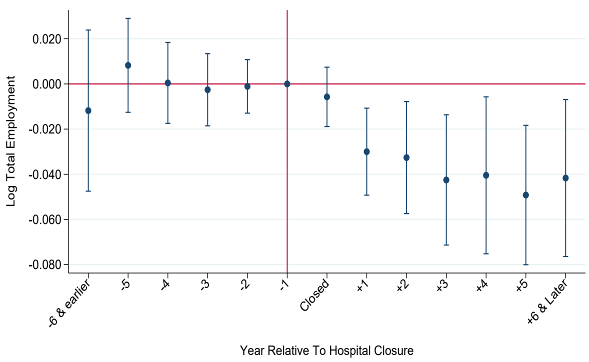
Figure A1: Rural County Classification and Location of Rural Hospital Closures



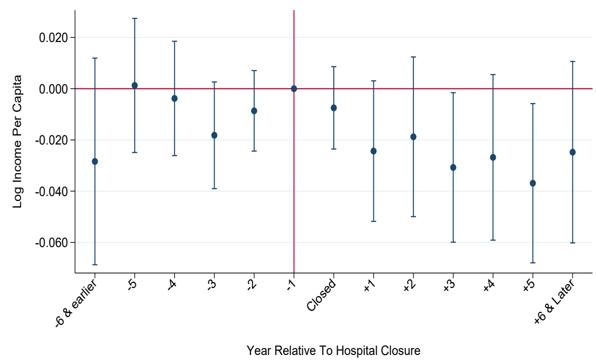
Notes: The above map shows rural and non-rural classifications of all U.S. counties. Counties are classified as rural if (1) more than 50 percent of the population live in a rural area or (2) the population density is under 64 persons per square mile for the entire county (10 acres per person) and the total population of the county is less than 50,000. Dropped rural counties are counties that do not have a hospital during the sample period.

Figure A2: Effects of Rural Hospital Closures on Service-Providing Industries

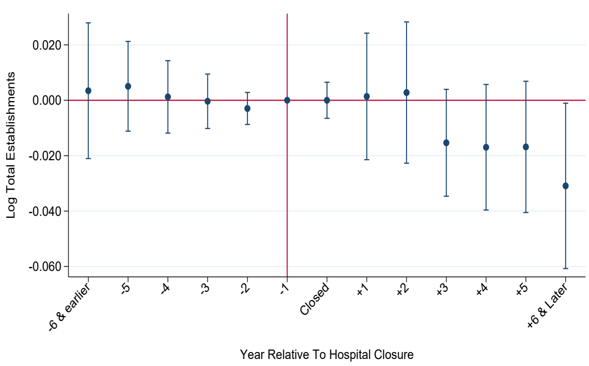
(a) Log Employment



(b) Log Per Capita Income



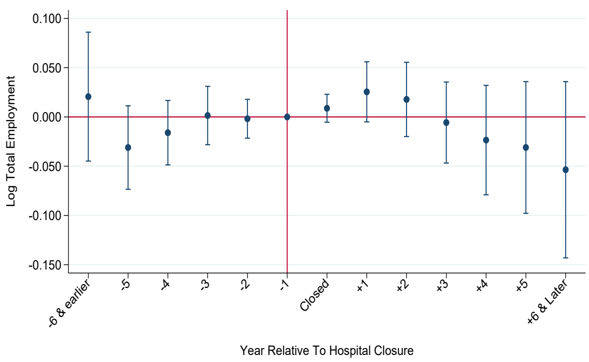
(c) Log Establishments



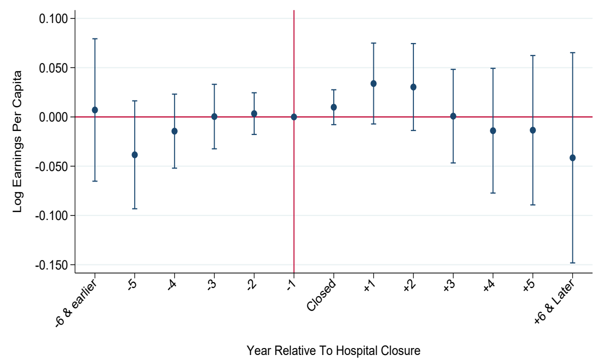
Notes: The above figures show event study plots of county-level income, employment, and establishment effects of rural hospital closures. The sample includes rural counties for 2003-2017. The longest vertical line indicates the end of the year before a hospital closure. Bands indicate 95 percent confidence intervals. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level.

Figure A3: Effects of Rural Hospital Closures on Goods-Producing Industries

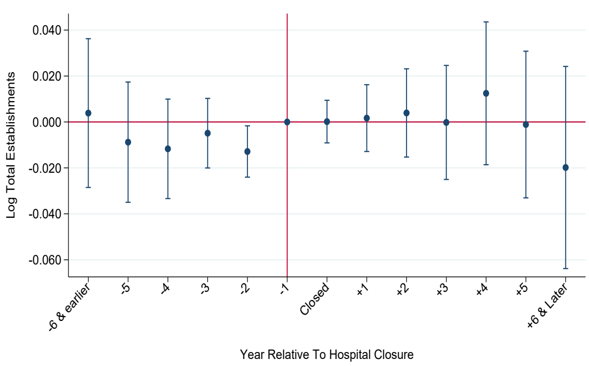
(a) Log Employment



(b) Log Per Capita Income



(c) Log Establishments



Notes: The above figures show event study plots of county-level income, employment, and establishment effects of rural hospital closures. The sample includes rural counties for 2003-2017. The longest vertical line indicates the end of the year before a hospital closure. Bands indicate 95 percent confidence intervals. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level.

Table A1: Hospital Characteristics: Closures vs. Non-Closures

Variable	Closed Hospitals	Never Closed Hospitals
Total Number of Beds	53.53	80.36
	(68.23)	(85.06)
Admissions per 100,000 pop.	4,888.30	6,538.30
	(7,115.41)	(7,575.65)
Inpatient Days per 100,000 pop.	38,504.38	58,685.71
	(70,493.70)	(100,205.30)
Full Time Personnel	179.88	377.73
	(394.61)	(420.92)
Expenses Per Inpatient Days	3,547.48	5,793.85
	(4,792.86)	(40,030.74)
Population Covered	35,157.54	32,757.09
	(29,650.61)	(34,735.97)
Number of Hospitals	97	2701

Notes: The table shows means and standard deviations in parentheses. Data are collected from the AHA Annual Survey. For closed hospitals, the statistics are are measured during years prior to closure. For never closed hospitals, the statistics are measured in 2003.

Table A2: AHA Alternative Registration Requirements

1) The primary function of the institution is to provide patient services, diagnostic and therapeutic, for particular or general medical conditions.
2) The institution shall maintain at least six inpatient beds, which shall be continuously available for the care of patients who are nonrelated and who stay on the average in excess of 24 hours per admission.
3) The institution shall be constructed, equipped, and maintained to ensure the health and safety of patients and to provide uncrowded, sanitary facilities for the treatment of patients.
4) There shall be an identifiable governing authority legally and morally responsible for the conduct of the hospital.
5) There shall be a chief executive to whom the governing authority delegates the continuous responsibility for the operation of the hospital in accordance with established policy.
6) There shall be an organized medical staff or fully licensed physicians that may include other licensed individuals permitted by law and by the hospital to provide patient care services independently in the hospital.
7) The medical staff shall be accountable to the governing authority for maintaining proper standards of medical care, and it shall be governed by bylaws adopted by said staff and approved by the governing authority.
8) Each patient shall be admitted on the authority of a member of the medical staff who has been granted the privilege to admit patients to inpatient services in accordance with state law and criteria for standards of medical care established by the individual medical staff. Each patient's general medical condition is the responsibility of the qualified physician member of the medical staff. When non-physician members of the medical staff are granted privileges to admit patients, provision is made for prompt medical evaluation of these patients by a qualified physician. Any graduate of a foreign medical school who is permitted to assume responsibilities for patient care shall possess a valid license to practice medicine, or shall be certified by the Education Commission for Foreign Medical Graduates, or shall have qualified for and have successfully completed an academic year of supervised clinical training under direction of a medical school approved by the Liaison Committee on GAT Medical Education.
9) Registered nurse supervision and other nursing services are continuous.
10) A current and complete medical record shall be maintained by the institution for each patient and shall be available for reference.
11) Pharmacy services shall be maintained in the institution and shall be supervised by a registered pharmacist.
12) The institution shall provide patients with food service that meets their nutritional and therapeutic requirements; special diets also shall be provided.

Notes: The table lists the alternative requirements for institutions licensed as a hospital by their appropriate state agency to be registered by the AHA. The source is the 2017 AHA Annual Survey Databook.

Table A3: Heterogeneous Effects by Number of Hospitals in County After Closure

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0 Hospitals After Closure	-0.073***	-0.050***	0.002	-0.043**	-0.029***	-0.019**	-0.026***
	(0.017)	(0.017)	(0.002)	(0.019)	(0.011)	(0.007)	(0.010)
$>$ 0 Hospitals After Closure	-0.024**	-0.011	0.002	-0.018*	0.003	-0.007	-0.005
	(0.010)	(0.011)	(0.001)	(0.010)	(0.011)	(0.006)	(0.007)
Mean 0 Hospitals	5,251	8,348	0.086	9,437	417	21,408	619
Mean $>$ 0 Hospitals	14,725	12,516	0.067	20,361	1,056	42,856	656
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829	1819
Observations	27429	27429	27433	27433	27433	27435	26968

Notes: This table shows estimated impacts of rural hospital closures by whether a county loses its sole hospital. Data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table A4: Heterogeneous Effects by Hospital Share of County Employment

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Above Median Emp. Share	-0.106***	-0.065***	0.003	-0.057***	-0.050***	-0.033***	-0.019**
	(0.015)	(0.016)	(0.002)	(0.018)	(0.010)	(0.007)	(0.009)
Below Median Emp. Share	0.006	0.005	0.002	-0.003	0.016	0.005	-0.011
	(0.011)	(0.013)	(0.001)	(0.012)	(0.013)	(0.007)	(0.008)
Mean Above Median	4,631	8,222	0.084	7,495	385	17,744	600
Mean Below Median	14,824	11,880	0.069	21,969	1,064	48,273	686
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829	1819
Observations	27429	27429	27433	27433	27433	27435	26968

Notes: This table shows estimated impacts of rural hospital closures by whether a closed hospital lies above or below the median contribution to the local economy. Data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively. Median employment=2.19 percent.

Table A5: Heterogenous Effects of Rural Hospital Closures on the Non-Hospital Sector

	Log Employment	*Log Total Estabs*	*Log Employment*	*Log Total Estabs*
	(1)	(2)	(3)	(4)
0 Hospitals After Closure	-0.029*	-0.025**		
	(0.016)	(0.011)		
> 0 Hospitals After Closure	-0.011	0.004		
	(0.010)	(0.011)		
Above Median			-0.057***	-0.046***
			(0.015)	(0.010)
Below Median			0.018	0.018
			(0.011)	(0.013)
Controls	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829
Observations	27416	27433	27416	27433

Notes: This table shows estimated impacts of rural hospital closures on the non-hospital sector by whether a county loses its sole hospital and by whether a closed hospital lies above or below the median contribution to the local economy. Data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table A6: Heterogenous Effects of Rural Hospital Closures on the Private Service-Providing Sector

	Log Employment	*Log Total Estabs*	*Log Employment*	*Log Total Estabs*
	(1)	(2)	(3)	(4)
0 Hospitals After Closure	-0.031*	-0.031**		
	(0.019)	(0.013)		
> 0 Hospitals After Closure	-0.022*	0.005		
	(0.012)	(0.013)		
Above Median			-0.056***	-0.053***
			(0.019)	(0.012)
Below Median			0.000	0.021
			(0.013)	(0.016)
Controls	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829
Observations	27361	27431	27361	27431

Notes: This table shows estimated impacts of rural hospital closures on the private service-providing sector by whether a county loses its sole hospital and by whether a closed hospital lies above or below the median contribution to the local economy. Data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table A7: Heterogenous Effects of Rural Hospital Closures on the Private Goods-Producing Sector

	Log Employment	*Log Total Estabs*	*Log Employment*	*Log Total Estabs*
	(1)	(2)	(3)	(4)
0 Hospitals After Closure	0.003	0.019		
	(0.036)	(0.019)		
> 0 Hospitals After Closure	-0.008	-0.008		
	(0.023)	(0.012)		
Above Median			-0.056	-0.014
			(0.036)	(0.017)
Below Median			0.046*	0.010
			(0.026)	(0.016)
Controls	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829
Observations	27320	27425	27320	27425

Notes: This table shows estimated impacts of rural hospital closures on the private goods-producing sector by whether a county loses its sole hospital and by whether a closed hospital lies above or below the median contribution to the local economy. Data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table A8: Amenity and Welfare Estimates Under Alternative Preference Assumptions

Households	Change in Amenities (1)	Change in Welfare (2)
Panel A: Baseline $s_i = 0.3$, $s_o = 0.6$		
Young Workers	0.005***	-0.004**
	(0.001)	(0.002)
Older Residents	-0.026**	-0.009**
	(0.011)	(0.004)
Weighted Total Change		-0.005**
		(0.002)
Panel B: Alternative $s_i = 0.1$, $s_o = 0.2$		
Young Workers	0.007***	-0.001*
	(0.002)	(0.001)
Older Residents	-0.020**	-0.003**
	(0.010)	(0.001)
Weighted Total Change		-0.002**
		(0.001)
Panel C: Alternative $s_i = 0.5$, $s_o = 1$		
Young Workers	0.003***	-0.006**
	(0.001)	(0.003)
Older Residents	-0.032**	-0.015**
	(0.014)	(0.006)
Weighted Total Change		-0.008***
		(0.003)

Notes: The above table shows how estimated changes in amenities and welfare for households vary by different values of the location preference parameters, s_i and s_o. Panel A depicts the baseline estimates when $s_i = 0.3$ and $s_o = 0.6$. Panel B shows estimates when when $s_i = 0.1$ and $s_o = 0.2$. Panel C shows estimates when when $s_i = 1$ and $s_o = 0.5$. The rows labeled *Weighted Total Change* calculated total household welfare losses weighted by population share of both household types. Standard errors calculated using the Delta Method. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Appendix B: Robustness and Alternative Specification Details

B.1 Decomposing the Difference-in-Differences Estimator

In the standard difference-in-differences model, the estimated treatment effect is equal to the difference between the change in outcomes in the treatment and control groups before and after the treatment occurs. When the treatment, such as the rural hospital closures analyzed in this study, vary over time, however, the difference-in-differences estimator is, as Goodman-Bacon (2018) shows, equal to a weighted average of all possible two-group/ two-period (2x2) estimators in the data. Furthermore, if the treatment effect changes over time, estimates derived from timing variations in the treatment bias the single coefficient estimator away from the sign of the true treatment effect.

To investigate the possibility of bias, I decompose the baseline difference-in-differences model into five groups of 2x2 estimators.[19] In Table B1, I summarize the results of the decomposition exercise for the main outcomes. Each row corresponds to a 2x2 estimator with corresponding weights reported in brackets below the estimates. The results reported in the table provides two key insights: first, approximately 94 percent of the baseline estimate is explained by comparisons between rural counties where no hospitals close and rural treatment counties. This finding is consistent with the large number of counties in the sample that do not experience a closure. Second, only 2 percent of the baseline estimator for each outcome is explained by timing variation among treatment groups, i.e. using counties with closures that occur later in the sample serving as the control group for an earlier treatment group and using counties treated earlier as the control group for later-closure counties. Thus, any bias in the overall difference-in-differences estimate caused by comparing late and early closures is small.

The remaining 4 percent of the baseline estimator is explained by the "residual component" that compares counties with the same treatment status but different *predicted* treatment based on the include covariates. Nearly all of the weight on the residual component comes from variation that is captured by state-by-year dummies included in the regression. The weights attributed to time-varying controls are less than 1 percent for each outcome, consistent with the fact that the point estimates derived using the baseline model move only slightly when controls are included. For

[19] The decomposition was derived using the Stata package *bacondecomp* (Goodman-Bacon et al., 2019).

most outcomes, the share of the baseline estimate that is explained by the residual component is small and consistent with the fixed-effects absorbing variation that may overstate the true treatment effect.

B.2 County-Industry Mix, Balanced Panel, and Population Weights

In Table B2, I show results derived from models that include a rich set of county-industry controls. Specifically, I adjust the baseline model by including the fraction of total employment and earnings for several industries, including education and health, business, natural resources, construction, manufacturing, trade, finance, and leisure. The estimates obtained including these controls closely resemble the results obtained from the baseline specification, evidence that the baseline results are not biased by unaccounted-for differences in the composition of local labor markets.[20]

I next estimate balanced-panel fixed-effects models. A concern with the baseline specification is that it includes counties that experienced a hospital closure in early or late years in the sample period. This un-balanced panel structure around closure years may give rise to composition bias in the estimates. To assess this concern, I exclude closure counties that do not include estimates for at least five years before and after the year of the closure. The results are presented in Table B3. I find similar effects to those indicated by the baseline estimates, suggesting that composition bias is not a key factor driving the main results.

In addition to including controls for county-industry mix and estimating balanced-panel models, I also estimate specifications that include county-population weights. The weighted least-squares (WLS) specification serves two main purposes. It serves first as a diagnostic check for model misspecification by simply comparing the WLS estimates with those obtained with the baseline ordinary least-squares (OLS) model. Second, including population weights is an informative way of gauging whether hospital closures have heterogeneous effects based on local population size. For example, if hospital closures have larger effects in more populated counties, then WLS estimation that places greater weight on more populous counties will tend to estimate larger effects than the OLS model. Table B4 shows the WLS results. The main takeaway is that the point estimates and standard errors are very similar to those of the baseline specification. This suggests that the OLS model is a good approximation of the true form of the conditional means of the outcome variables and that there is relatively little underlying heterogeneity in the treatment effects that

[20]Note that the smaller sample sizes relative to those used with the baseline model results from QCEW data suppression for specific industries.

are attributable to population size in counties where hospitals close.

B.3 County-Specific Linear Trends

As discussed in Section 4.2, a key identifying condition that must be satisfied for estimating unbiased, causal effects of rural hospital closures on local labor markets is that underlying variations in outcome trends are not correlated with the treatment. Neither studies exploring why hospitals close nor the event study analysis provide evidence that correlations between outcome trends and hospital closures introduce significant bias to the results. Nevertheless, a common approach used to test for pre-treatment variations in outcome trends is to adjust for unit-specific linear trends in the regression models. Including unit-specific trends makes it possible to control for unobserved heterogeneity in the outcome that evolves linearly over time and that might be correlated with the treatment status.

There is, however, a potentially high cost associated with including unit-specific trends. In the context of this study, if a hospital closure affects the growth rate rather than the level of the outcome variable, then specifications that include county-specific trends will mechanically attenuate estimates of the closure effect, leading to higher probabilities of type II error. This is a particularly relevant problem when the treatment effects appear gradually after treatment, for which I find evidence for total establishments and population. Indeed, there is now a substantial body of literature that recommends against including unit-specific trends, especially when using event study and difference-in-differences estimation strategies.[21]

As an alternative to including county-specific trends, I follow the suggestion of Meer and West (2016) and control for pre-reform trends in each county rather than for an average trend.[22] Specifically, I construct county-level trends by extrapolating estimated linear pre-reform trends to the post reform years and including the predicted time trends as controls. The results are shown in Table B5 and are consistent with the baseline estimates. This is not surprising considering the flat pre-trends derived from the event study analysis.

[21] See Wolfers (2006), Baum-Snow and Lutz (2011), Lee and Solon (2011), Fadlon and Nielsen (2015), Meer and West (2016), Borusyak and Jaravel (2017).

[22] Other papers that use this approach include Sjögren (2010) and Böhlmark and Lindahl (2015)

B.4 Propensity-Score Reweighting

To improve balance between closure and non-closure counties and provide robustness checks of the results based on the full analysis sample, I also estimate difference-in-differences models in combination with propensity-score reweighting. The first step is to estimate the propensity score for hospital closures. I follow Imbens and Rubin (2015) and use an iterative procedure to select covariates and second-order terms from a rich set of pre-treatment county characteristics measured in 2000 to include in the propensity score.[23] The selection procedure starts with a logit propensity-score model with just an intercept and adds each of the remaining covariates, one at a time, to the model.[24] I then estimate the model and calculate the likelihood ratio statistics, assessing the null hypothesis that the newly included covariate has a zero coefficient. After repeating this exercise for all potential covariates, I add the covariate with the highest likelihood ratio statistic to the specification and start the process again with the remaining covariates and continue until all the likelihood ratio statistics are less than 1. For quadratic terms involving the first-order covariates, the iterative procedure is repeated and includes an additional second-order term until all of the remaining likelihood ratio statistics are less than 2.71.[25]

Once the procedure has selected the covariates, the propensity score is estimated using the following logistic regression model:

$$Logit(Pr(HospitalClosure_c)) = \beta_0 + \beta_1 \mathbf{X}_{2000c}, \tag{22}$$

where the dependent variable is an indicator of whether county c experiences a hospital closure

[23]The first- and second-order covariates chosen for potential inclusion in the propensity-score model include the average unemployment rate, total employment, average household income, total wage and salary income, total establishments, labor force participation, percentage of residences below the poverty level, total population and in four age groups (1-19, 20-39, 40-64, 65 and over), total male population and in four age groups (1-19, 20-39, 40-64, 65 and over), total female population and in four age groups (1-19, 20-39, 40-64, 65 and over), total white population and in four age groups (1-19, 20-39, 40-64, 65 and over), total black population and in four age groups (1-19, 20-39, 40-64, 65 and over), total population of other races and in four age groups (1-19, 20-39, 40-64, 65 and over), total Hispanic population and in four age groups (1-19, 20-39, 40-64, 65 and over), total county square miles, population density, percentage urban population, percentage of rural population, total occupied housing units, total vacant housing units, average rent, and average housing value.

[24]The selection procedure also allows for automatic inclusion of covariates in the propensity score model that are viewed as essential for explaining the treatment and related to outcome measures. I did not choose to automatically include any covariates.

[25]The selected covariates include the percentage of residences below the poverty level, the percentage of rural population, total vacant housing units, total female population 1-to-19 years of age, total non-white and non-black population 1-to-19, 20-to-39, and 40-to-64 years of age, the quadratic of the percentage of residences below the poverty level, total non-white and non-black population 1-to-19 years of age interacted with the percentage of residences below the poverty level, and the quadratic of total non-white and non-black population 20-to-39 years of age.

during my sample period. Figure B1 illustrates the distribution of the estimated propensity scores using kernel density and histogram plots. I trim observations with propensity scores outside the overlap region (.007, .346), as they have no comparable counterparts in the closure sample. After trimming the sample, I re-estimate equations 1 and 2 and weight the estimates by $T+(1-T)\times\frac{p}{(1-p)}$, where T is an indicator for the treatment and p is the estimated propensity score. Weighting in this way provides a consistent estimator of the average treatment effect on the 97 treated counties in my sample (ATT). The results obtained using the trimmed, reweighted sample are shown in Table B6 and are very similar to my baseline results.

B.5 County Border-Pair Design and Excluding Border Counties

I next explore how results change after *including* only rural counties that border closure counties in the control group as well as after *excluding* border counties from the analysis. There are valid arguments for and against these alternative approaches. On the one hand, neighboring counties are presumably more similar to one another across observable and non-observable characteristics, strengthening the validity of the estimates and providing an informal test as to whether the baseline results are confounded due to differences in local economic and demographic conditions across space. On the other hand, there is a concern that border counties are themselves likely to be affected by a neighboring hospital closure. By including border counties in the control group, these spillovers (if positive) may dilute the true effect of hospital closures on the local economy. To investigate these competing arguments, I estimate a (1) county border-pair specification following Dube et al. (2010) and Borgschulte and Cho (2019) and (2) the baseline specification that excludes border counties from the control group.

To implement the county border-pair specification, I drop all non-border rural counties from the control group and add border-pair-by-year fixed effects to the regression specifications. I weight the estimates by the inverse of appearances in the sample to account for the fact that closure counties can pair with multiple other control counties. Following Cameron et al. (2011), standard errors are two-way clustered at the county and pair level. The results are shown in Table B7, while estimates from the specification that excludes border counties are shown in Table B8. When compared to one another, the adverse effects on employment, labor force participation, establishments, population, and rents are larger in specifications where border counties are excluded from the analysis. This result is consistent with the notion that positive spillovers to neighboring counties lead to an underestimation of the true effect of hospital closures when border counties are included in the control sample. Still, the estimated effect sizes derived from both specifications are largely consistent with the baseline results, suggesting that the degree of attenuation from including border counties is marginal.

B.6 Effects of Urban Hospital Closures

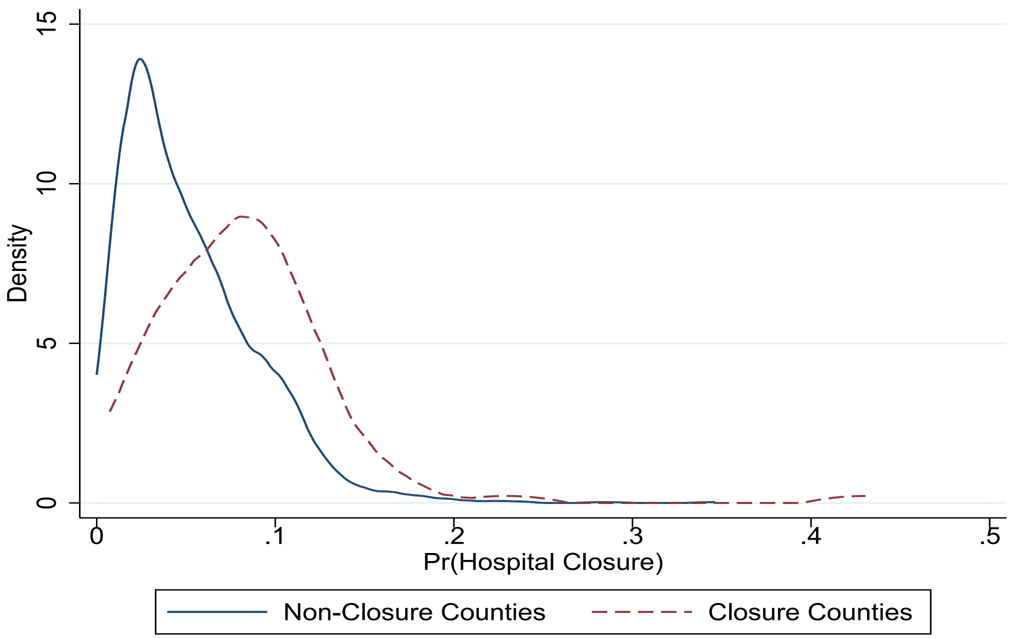
It is informative to compare how the effects of hospital closures on local labor markets differ between urban and rural areas. In the final alternative specification, I estimate the effects of hospital closures in urban counties. I am unaware of any studies that have focused on the local labor market effects of urban hospital closures.[26] There is reason to believe that urban hospital closures should have a much smaller effect on a local labor market than rural hospital closures. In particular, urban areas have a greater capacity to absorb employees and patients as a result of having a larger number of proximate surrounding hospitals.

I use two specifications to estimate the effects of urban hospital closures. The first is a baseline fixed-effects model that mirrors the rural hospital analysis described in Section 4. Urban counties are defined as all counties in the sample that are not classified as rural. Table B9 shows the results. I find little evidence that urban hospital closures have a significant impact on a local economy. The majority of the estimates are near zero and statistically insignificant. To account for differences between closure and non-closure counties, I also estimate models using propensity-score reweighting in the manner described in section B.4. The estimates, shown in Table B10, are similarly small and not statistically different from zero.

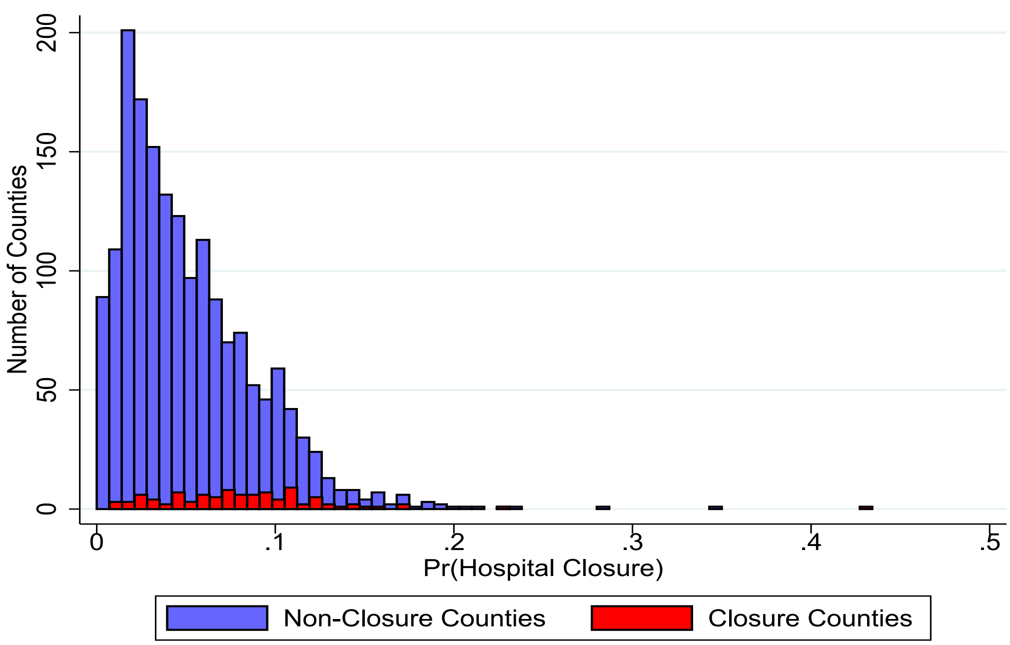
[26]There are, however, several papers that study the relationship between urban hospital closures and other outcomes, such as hospital efficiency (Lindrooth et al., 2003), welfare (Capps et al., 2010), and mortality (Buchmueller et al., 2006).

Figure B1: Propensity Score Distribution

(a) Kernel Density



(b) Histogram



Notes: The above figures illustrate the kernel densities and histograms of the propensity scores for rural closure and non-closure counties.

Table B1: Difference-in-Differences Estimator Decomposition

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Timing Comparisons	-0.024	-0.019	0.001	-0.007	0.008	-0.001	-0.004
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
Always vs. Timing	-0.142	-0.110	0.009	-0.119	0.009	-0.009	0.017
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Never vs. Timing	-0.049	-0.045	0.002	-0.031	-0.018	-0.008	-0.003
	[0.938]	[0.938]	[0.938]	[0.938]	[0.938]	[0.938]	[0.938]
Always vs. Never	-1.024	2.605	0.224	0.384	-0.291	0.294	-1.765
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Within Comparisons	0.094	0.415	0.003	0.048	0.190	-0.111	-0.276
	[0.039]	[0.039]	[0.039]	[0.039]	[0.039]	[0.039]	[0.039]
Mean Dependent Variable	10,473	10,680	0.075	15,421	769	33,109	641
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829	1819
Observations	27429	27429	27433	27433	27433	27435	26968

Notes: This table shows results from a difference-in-differences estimator decomposition using data from the AHA Annual Survey between the years 2003 and 2017. Each row corresponds to a 2x2 estimator with corresponding weights reported in brackets below the estimates. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B2: Robustness: Controls for County Industry Mix

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.039***	-0.035***	0.002**	-0.026***	-0.004	-0.010**	-0.009
	(0.009)	(0.008)	(0.001)	(0.008)	(0.009)	(0.005)	(0.006)
Mean Dependent Variable	10,919	11,074	0.074	15,800	794	34,243	650
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Mix Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1712	1712	1712	1712	1712	1712	1701
Observations	23291	23291	23289	23289	23291	23291	22909

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls for industry mix include the fraction of county employment and earnings for the following industries: education and health, business, natural resources, construction, manufacturing, trade, finance, and leisure. Demographic controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B3: Robustness: Balanced Panel

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.041***	-0.024*	0.003**	-0.024	-0.011	-0.011	-0.016**
	(0.016)	(0.014)	(0.001)	(0.016)	(0.011)	(0.007)	(0.007)
Mean Dependent Variable	10,898	12,423	0.064	15,685	820	32,803	650
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1770	1770	1770	1770	1770	1770	1760
Observations	26544	26544	26548	26548	26548	26550	26083

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B4: Robustness: Population Weighted

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.038***	-0.018**	0.001	-0.034***	-0.009	-0.020***	-0.012*
	(0.009)	(0.009)	(0.001)	(0.010)	(0.009)	(0.007)	(0.006)
Mean Dependent Variable	22,726	12,772	0.067	33,679	1,668	69,553	716
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829	1819
Observations	27429	27429	27433	27433	27433	27435	26968

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. Regressions and mean dependent variables weighted by county population. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B5: Robustness: County-Specific Trends

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.038***	-0.025***	0.002*	-0.019***	-0.002	-0.008**	-0.012**
	(0.008)	(0.009)	(0.001)	(0.007)	(0.007)	(0.003)	(0.005)
Mean Dependent Variable	10,473	10,680	0.075	15,421	769	33,109	641
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1829	1829	1829	1829	1829	1829	1819
Observations	27429	27429	27433	27433	27433	27435	26968

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county fixed effects, state-by-year fixed effects, and county-specific trends. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B6: Robustness: Propensity-Score Reweighting

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.045***	-0.035***	0.003***	-0.025***	-0.007	-0.007*	-0.010*
	(0.008)	(0.008)	(0.001)	(0.008)	(0.007)	(0.004)	(0.005)
Mean Dependent Variable	10,962	11,272	0.072	15,870	800	34,664	643
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1738	1738	1738	1738	1738	1738	1730
Observations	26066	26066	26068	26068	26070	26070	25633

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. Regressions and mean dependent variables weighted by $T + (1 - T) \times \frac{p}{(1-p)}$, where T is an indicator for treatment and p is the estimated propensity score. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B7: Robustness: County Border-Pair Design

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.039***	-0.024**	0.002***	-0.024***	-0.004	-0.007*	-0.009
	(0.008)	(0.010)	(0.001)	(0.007)	(0.007)	(0.004)	(0.006)
Mean Dependent Variable	10,869	11,347	0.072	15,801	780	34,611	667
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Border-Pair x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	378	378	378	378	378	378	378
Observations	11334	11334	11340	11340	11340	11340	11238

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county fixed-effects, state-by-year fixed effects, and county border-pair-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are two-way clustered at the county and border-pair levels. Regressions and mean dependent variables weighted by number of county appearances in the sample. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B8: Robustness: Excluding Adjacent Counties

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.042***	-0.023**	0.002*	-0.028***	-0.011	-0.014***	-0.012**
	(0.010)	(0.010)	(0.001)	(0.011)	(0.009)	(0.005)	(0.006)
Mean Dependent Variable	10,829	10,719	0.072	15,971	791	33,925	666
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1497	1497	1497	1497	1497	1497	1487
Observations	22452	22452	22453	22453	22453	22455	22038

Notes: This table shows estimated impacts of rural hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B9: Effects of Urban Hospital Closures

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.009	-0.005	-0.001**	0.007	0.003	-0.006	-0.006
	(0.006)	(0.006)	(0.001)	(0.006)	(0.006)	(0.006)	(0.006)
Mean Dependent Variable	156,884	20,781	0.063	173,703	9,828	344,517	894
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	682	682	682	682	682	682	660
Observations	10230	10230	10218	10218	10230	10230	9833

Notes: This table shows estimated impacts of urban hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed-effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Table B10: Effects of Urban Hospital Closures: Propensity-Score Reweighting

	Log Employment	*Log Per Capita Income*	*Unemployed Rate*	*Log Labor Force*	*Log Total Estabs.*	*Log Total Population*	*Log Median Rents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospital Closure	-0.003	-0.002	-0.001	0.007	0.001	0.001	0.003
	(0.006)	(0.006)	(0.001)	(0.006)	(0.006)	(0.005)	(0.006)
Mean Dependent Variable	225,177	23,664	0.065	234,610	13,413	462,801	944
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	639	639	639	639	639	639	616
Observations	9585	9585	9573	9573	9585	9585	9197

Notes: This table shows estimated impacts of urban hospital closures using data from the AHA Annual Survey between the years 2003 and 2017. All specifications include county and state-by-year fixed-effects. Controls include the county population percentages of the 1 to 19, 20 to 39, 40 to 64, and over 65 years age ranges, the county population percentages of two racial groups (white, non-white), the county population percentages of males, and the county population percentages of Hispanics. Standard errors are clustered at the county level. Regressions and mean dependent variables weighted by $T + (1 - T) \times \frac{p}{(1-p)}$, where T is an indicator for treatment and p is the estimated propensity score. *, **, and *** indicate significance levels of .10, .05, and .01., respectively.

Appendix C: Spatial Equilibrium Model Details

(1) **Worker's Problem**: The maximization problem can be written in terms of a Lagrangian function:

$$L_{ict} = \alpha ln h_{ict} + \beta ln X_{ict} + ln A_{ct} + \epsilon_{ict} + \lambda(w_{ct} - r_{ct} h_{ict} - p_{ct} X_{ict}).$$

Taking derivatives with respect to housing and goods yields the following first-order conditions:

$$\frac{\partial L_{ict}}{\partial h_{ict}} = \frac{\alpha}{h_{ict}} - \lambda r_{ct} = 0,$$
$$\implies h_{ict} = \frac{\alpha}{\lambda r_{ct}}.$$

$$\frac{\partial L_{ict}}{\partial X_{ict}} = \frac{\beta}{X_{ict}} - \lambda p_{ct} = 0,$$
$$\implies X_{ict} = \frac{\beta}{\lambda p_{ct}}.$$

$$\frac{\partial L_{ict}}{\partial \lambda} = w_{ct} - r_{ct} h_{ict} - p_{ct} X_{ict} = 0.$$

Plugging the first-order conditions for h_{ict} and X_{ict} into the utility function yields the indirect utility of each worker shown by equation 5.

(2) **Older Resident's Problem**: The maximization problem can be written in terms of a Lagrangian function:

$$L_{oct} = \alpha ln h_{oct} + \beta ln X_{oct} + ln A_{ct} + \epsilon_{oct} + \lambda(w_c - r_{ct} h_{oct} - p_{ct} X_{oct}).$$

Taking derivatives with respect to housing and goods yields the following first-order conditions:

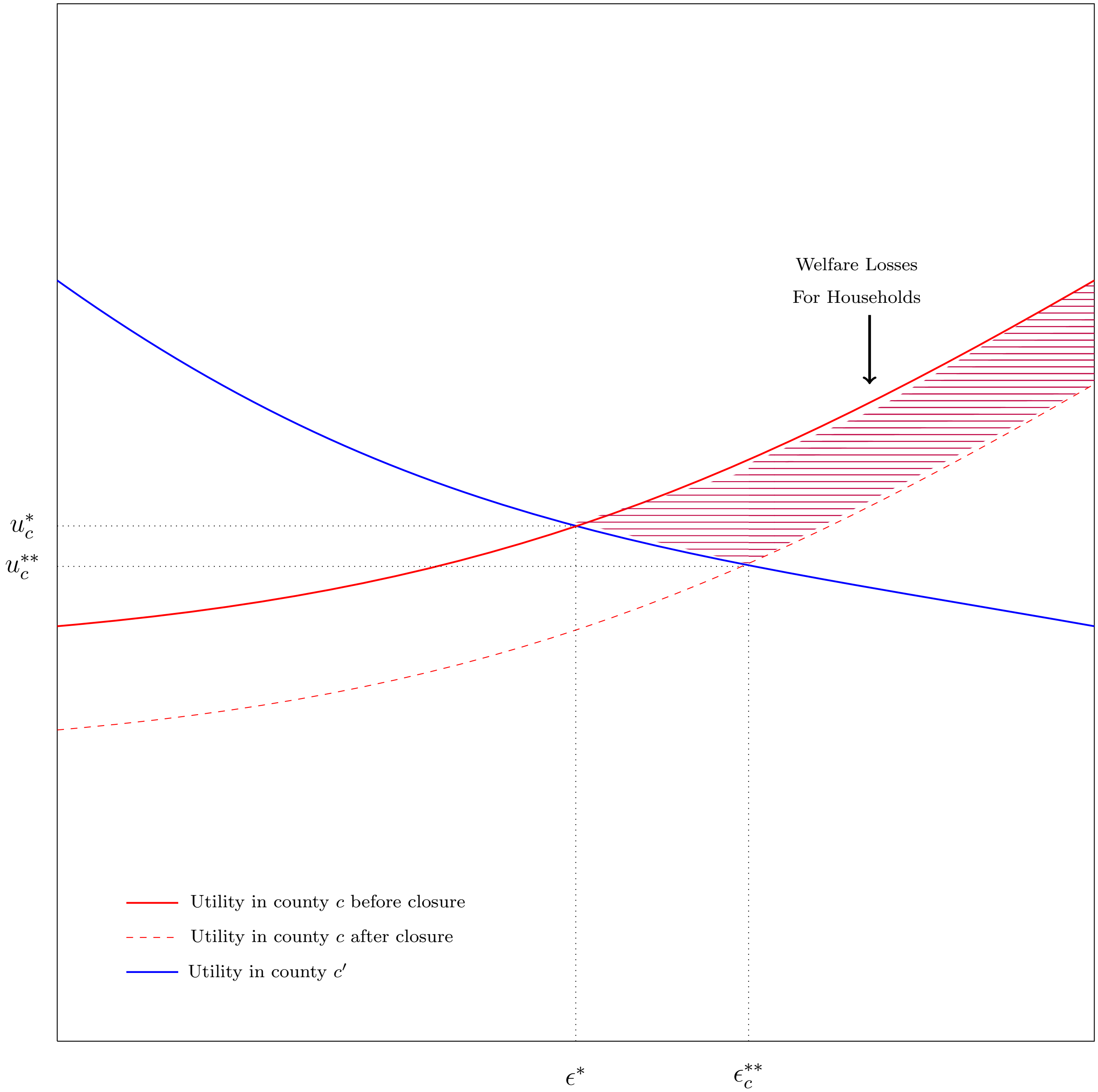
$$\begin{aligned}\frac{\partial L_{oct}}{\partial h_{oct}} &= \frac{\alpha}{h_{oct}} - \lambda r_{ct} = 0,\\ \implies h_{oct} &= \frac{\alpha}{\lambda r_{ct}}.\end{aligned}$$

$$\begin{aligned}\frac{\partial L_{oct}}{\partial X_{oct}} &= \frac{\beta}{X_{oct}} - \lambda p_{ct} = 0,\\ \implies X_{oct} &= \frac{\beta}{\lambda p_{ct}}.\end{aligned}$$

$$\frac{\partial L_{oct}}{\partial \lambda} = -r_{ct} h_{oct} - p_{ct} X_{ict} = 0.$$

Plugging the first-order conditions for h_{oct} and X_{oct} into the utility function yields the indirect utility shown by equation 7.

Figure C1: Changes in Household Utility Following Rural Hospital Closures



Notes: The above figure illustrates how household utility changes after a rural hospital closure in location c. The x-axis represents marginal preferences for living in location c. The y-axis represents the utility of each household in location c. Preferences for location c are increasing from left to right.