Short-Term Economic Impact of Rural Hospital Closures

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Many rural hospitals across the United States are being forced to shut their doors, leading to questions about effects on local economies. This paper uses average treatment effects and difference in differences methodology to quantify the short-term impacts of closures, focusing on variables such as income, poverty, unemployment, home values, and shifts in industry employment. The likelihood of a hospital closure in a county was estimated and these propensity scores were then used to match the 43 counties that experienced a rural hospital closure with 'otherwise similar' counties whose hospitals did not close. Results suggest that recent rural hospital closures significantly impact many economic variables as well as creating shifts in occupations and industry.

Key Words: Rural Development, Health and Economic Development, Hospital Closures, Propensity Score Analysis

Introduction

Hospitals in rural areas are an essential part of the economic foundation of the community in which they reside. Rural communities fear that hospital closures will bring about many negative impacts to the community, among those fears include negative economic consequences, declines in the level of health care provided, and an increased inability to bring in new industries to the area. (Probst et al. 1999)

A recent report from *Rural Health Information* classifies 673 rural hospitals as vulnerable for closure, with those hospitals being located across 42 different states. Of the 673 hospitals vulnerable for closure, 68% are classified as critical access hospitals (CAHs), a designation for rural hospitals by the Centers for Medicare and Medicaid Services which is based on size, distance from other providers, average length of stay, and the capacity to provide twenty-four/seven emergency care services (Hub 2016). Southern states are disproportionately more likely to be affected due to the higher number of rural areas in these states. Long term estimates of the economic impact of these rural hospital closures are that if all 673 hospitals vulnerable for closure were to close, the economic impact would be a loss of 99,000 healthcare jobs and a $277 billion loss to GDP (Ellison 2016).

As hospitals are closing across the country and communities fear the possible economic impacts of a closure, many localities will search for new sources of funding to sustain their hospitals. Many communities have raised taxes to generate the funds needed to keep hospital doors open. Choosing between letting a hospital close and raising taxes and other sources of funding to keep hospitals open, needs to be based on full information of both the short and long term effects of a closure. With a firm understanding of the effects of closures, hospitals can be

more aggressive in lobbying the community for funding. As stated by Nemes (1990), "Rural hospitals have got to get more aggressive in describing to their communities how vital the hospital is to local healthcare needs and the local economy (p. 1)." Equipped with more knowledge, hospitals will better position themselves to make an aggressive argument (Nemes 1990). When considering generating revenue for a hospital the costs and benefits must be closely examined. Whether the revenue generated for the hospital be from sales taxes, property taxes, or one of the many other instruments for revenue generation at the community level, the benefits of implementing the revenue instrument must outweigh the costs to the community (Rothkopf, Harstad, and Fu 2003).

Studies on the economic impact of rural hospital closures mostly focus on long term (5 to 10 years) economic impacts (e.g. Holmes et al. 2006 and Probst et al. 1999). Furthermore, previous studies have had limited focus on the possibility that the industries and occupations of workers in counties where rural hospitals closed might be dramatically impacted. Given the previous studies findings, this presents two topics of interest for the economic impacts of rural hospital closures: 1) determining the short-term (2 years) economic impacts of rural hospital closures and 2) determining the shifts in the employment of those affected as measured by changes in occupation and industry classification. This paper attempts to provide insight on these two topics using county-level data from 42 rural hospital closures between 2010 and 2012. Two econometric techniques, average treatment effect and difference in differences, are used to assess whether a rural hospital closure had significant economic impacts at the county-level.

Information on twenty-six economic measures (eight on general county economic factors, five on occupational employment information, and thirteen on industry employment information) gathered for both those counties that did experience a hospital closure and those that did not is

used to the nature of the potential impact. In the review that follows, this paper establishes that a limited number of studies focused on short-term economic impacts of rural hospital closures, and that there is little research on how such closures might affect local industrial and occupational employment. No studies that the author is aware of use multiple techniques to assess the robustness of the findings. The data and procedural methods of the study are then presented, including basic descriptive statistics. The results of the methods are reviewed and compared, and the article concludes with an overview of the findings.

Literature Review

The importance of hospitals to the economic well-being and function of a rural economy is recognized in a wide variety of economic literature. Hospitals are the second largest source of private sector jobs, employ nearly 5 million people, and spend an estimated $702 billion on goods and services from outside businesses (Association 2013). A wide array of literature examines this relationship of a hospital closure to economic variables over many differing time frames, using varying methods.

Probst et al. (1999) discovered that rural communities experiencing a hospital closure were expected to have a lower growth of income in the year and two years following a closure, compared to those communities that did not experience a closure, but found these differences to be insignificant. It was also found that unemployment behaved similar to income in communities experiencing a closure, falling below the levels of communities that did not experience a hospital closure, but insignificant in their magnitude (Probst et al. 1999).

The ten year economic impact of a rural hospital closure was examined by Holmes et al., focusing on variables of income and unemployment rates. These findings found that per-capita

income was reduced by $703 and that unemployment increased by 1.6 percentage points, both of which were significant. While this study examined the long term effects, it was also noted that short term effects would be expected to be similar. This study also examined the effects of multiple sources of hospital care in a community, which was found to mitigate the long term economic impact of a closure (Holmes et al. 2006). The economic impact of closure on the states of Georgia, Tennessee, and Texas for the time period of 1998-2000 was conducted by Ona et al. (2007). In this study the authors find no significant impacts of a hospital closure when studied over a three year period. The three year period was chosen based on available data and the expectation that the impact of a closure should be detectable within three years (Ona, Hudoyo, and Freshwater 2007).

Miller et al. (2015) introduced a new variable into the study of the impact of rural hospital closures by examining the impact a closure has on rural housing values. Following the underlying assumption that rural hospitals can serve as an amenity to attract home buyers, they examined how home values changed following a closure based on the distance of the sale to the hospital. This paper found that the change in housing values was not significantly affected by the closure of a hospital (Miller, Nikaj, and Pender 2015).

Data

Data on the number of rural hospital closures come from the North Carolina Rural Health Research Program. This data list 76 rural hospital closures for 2010-2016, the data was truncated to only include the years 2010-2012 to be able to measure a consistent effect of two years following closure. The years 2010 and 2012 were chosen because of the availability of all data; both covariates and outcome variables were available at a consistent interval. The 43 hospitals

closed during this period are represented in Figure 1. Data on county level economic measures come from the U.S. Census Bureau's American Community Surveys and supplemental surveys. The economic variables of interest as well as information on occupational and industry employment are included in Table 1. Data for the explanatory variables includes 1) natural log of Medicaid Participants; 2) Medicaid participants making more than one visit per year; 3) state political affiliation; 4) number of unhealthy days; 5) percent of smokers; 6) percent obese; 7) binge drinkers; 8) number of diabetics treated; 9) Rural Urban Continuum Code; 10) discharges for ambulatory sensitive conditions; and 10) percent of county that is black.

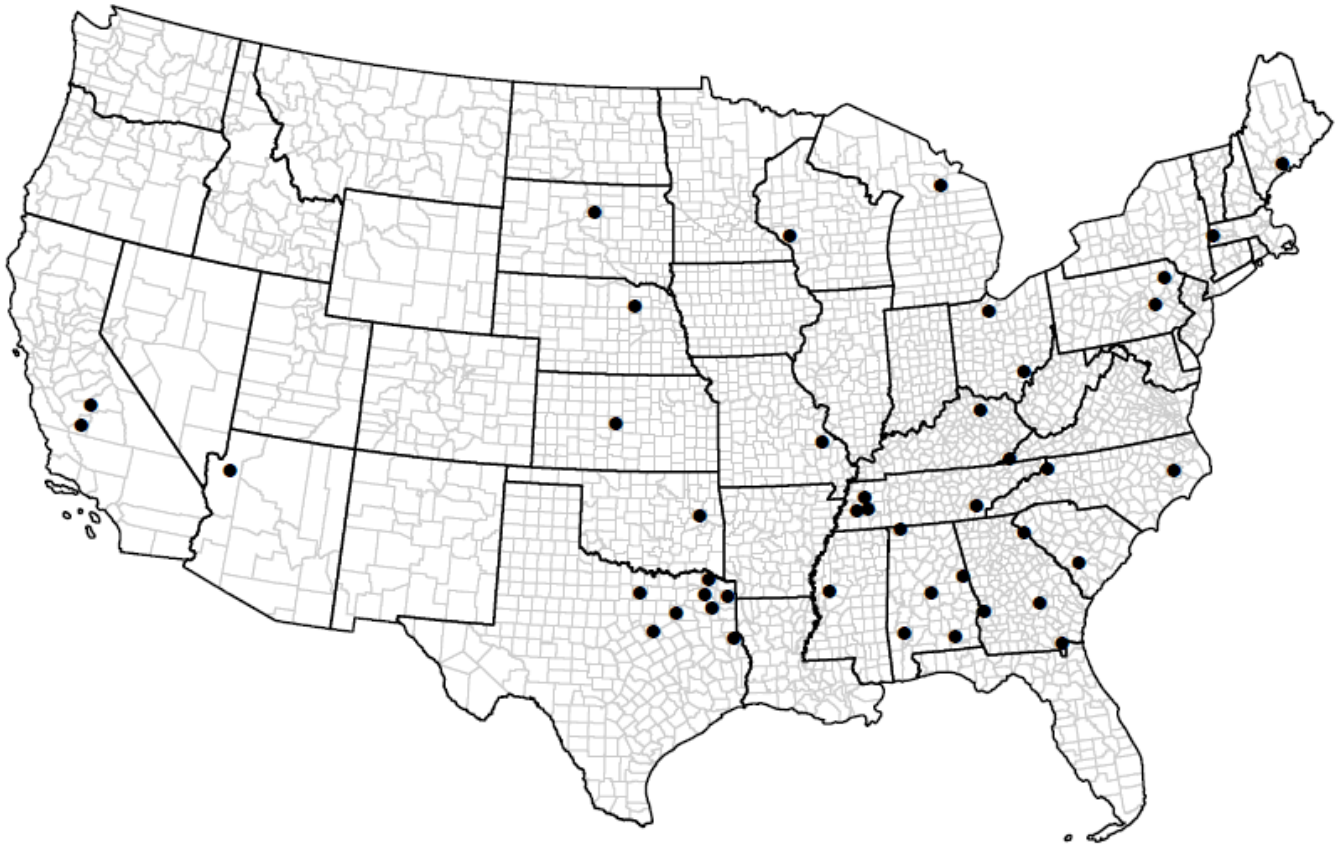

Figure 1. Location of Rural Hospital Closures: 2010-2012

Table 1. Dependent Variable Summary Statistics: Means (Treated=Hospital Closure)

	Change 2012-2014	
Outcome Variable	Treated	Untreated
General Variables		
Poverty level (%)	-8.44	-9.19
Mean income	1269.65	1765.79
Median income	245.46	925.78
Unemployment level	0.21	-0.06
Mean travel time	0.29	0.12
Worked at home	24.93	63.98
Median rent	16.06	27.96
Median home value	-90.69	-712.68
Occupation		
Management, business, science, and arts	41.62	425.39
Service occupations	245.48	77.11
Sales and office occupations	-126.90	-123.65
Natural resources, construction, and maintenance occupations	-137.76	-96.88
Production, transportation, and material moving occupations	30.90	50.90
Industry		
Agriculture, forestry, fishing and hunting, and mining	-7.46	35.07
Construction	-119.21	-119.08
Manufacturing	7.86	-39.55
Wholesale trade	-40.51	-25.30
Retail trade	-23.97	59.65
Transportation and warehousing, and utilities	-26.02	-8.17
Information	-52.48	-23.10
Finance and insurance, and real estate and rental and leasing	-0.41	-33.15
Professional, scientific, management, administrative and waste management services	67.60	161.50
Educational services, and health care and social assistance	37.88	258.79
Arts, entertainment, and recreation, and accommodation and food services	60.20	187.89
Other services, except public administration	24.11	29.90
Public administration	-41.60	16.79

Source: The 2012 data is from the United States Census 2012 American Community Survey (https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_12_1YR_CP03&prodType=table) and the 2014 data is from the United States Census 2014 American Community Survey (https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_14_1YR_DP03&prodType=table)

Methods and Procedures

This research attempts to answer the question of whether a rural hospital closure over the period 2010-2014 experienced short-term (2 year) economic decline or a shift in industry and occupational employment. Two different methods, average treatment effect and difference in difference analysis incorporating propensity score matching are used for the analysis. The methods differ in their assumptions; comparing the results will provide a way to test the robustness of the findings.

Average Treatment Effect on the Treated (ATET)

Regression analysis can provide insight about the correlation of a hospital closure and various short-term economic impacts, but cannot establish causality. Propensity score analysis and matching techniques has become an increasingly popular method to address this issue. While controversy in the literature still remains on the use of propensity score analysis and its use in asserting causality, it remains one of the most popular methods for non-controlled experimental studies (Caliendo and Kopeinig 2008). These techniques are model-unbiased and therefore do not have restrictive assumptions commonly associated with OLS concerning (Imbens 2004). The ATET is the difference between the outcome of the treated observations and the outcomes of the non-treated observations if they had in fact had received treatment (hospital closure). The ATET can be measured as

$$(1) \qquad ATET = E(\Delta|T = 1) = E(y_1|x, T = 1) - E(y_0|x, T = 1)$$

where *T*=1 for counties that experienced a hospital closure and zero for those counties that did not, y_1 is a treated county, or a county that experienced a hospital closure, y_0 is a county that did not experience a hospital closure, and x is the measured covariates of the propensity score

estimation. We can observe $E(y_1|x, T = 1)$, but cannot observe $E(y_0|x, T = 1)$, and thus this counterfactual observation must be estimated. To accomplish this we need to match counties that did experience a hospital closure with otherwise similar counties that did not. The first step is to estimate the propensity score, or the probability that a county will experience a hospital closure is true. The propensity score is estimated with a probit model, as the conditional probability of experiencing a hospital closure is modeled on observable predictors that are independent of the measured outcomes. The distribution of the propensity score must be checked for balance as well, that is for each covariate the means of the treated and controls are statistically different following matching. Once the propensity score is estimated, it is used to match treated and non-treated counties with similar likelihoods of closing. Literature suggests using multiple matching techniques; this paper uses nearest-neighbor, radius matching, and kernel matching techniques, developed by (Becker and Ichino 2002). Nearest neighbor matching matches by minimizing the distance between treated and non-treated counties. Radius matching sets a bound or radius on the distance that a treated observation can be from a non-treated to be considered similar. Both of these techniques can vary in terms of the number of matches that are found. Kernel matching solves this problem by using all observations in the control group, but weighting them so that nearer matches for each treated observation gets the most weight. After matching on propensity score the ATET becomes

$$ATET = E(\Delta|p(x), T = 1) = E(y_1|p(x), T = 1) - E(y_o|p(x), T = 0) \quad (2)$$

where $p(x)$ is now representative of the propensity score as a function of the covariates x.

Difference in Differences (DID)

The difference in differences model can be applied when panel data is available both before and after the treatment occurs. This model is an improvement over the one period model. This method is applied in a similar matter to ATET, but also takes into account the differences in time periods. The difference in differences model for the time period 2012 -2014 can be expressed as

(3) $$ATET = E(y_{1a} - y_{1b}|x, T = 1) - E(y_{0a} - y_{0b}|x, T = 1)$$

where the only difference becomes that the model takes into account the observations both before and after closure where y_{1a} is a measure for a county after a closure that received treatment, y_{1b} is a measure for a county before a closure that received treatment, y_{0a} is a measure for a county after a closure that did not received treatment, and y_{0b} is a measure for a county before a closure that did not received treatment. This analysis also uses all three matching techniques (nearest neighbor, radius, and kernel).

Results

Average Treatment Effect

To generate the propensity scores for rural hospital closures, the likelihood of a county experiencing a hospital closure is modeled by a probit regression. Independent variables include 2012 information, as to predate the closed hospitals in this study, shown in Table 2 along with the full results of the probit model. The final specification used for the study has a pseudo R^2 of 0.094 and satisfies the balancing property among the covariates for treated and non-treated

groups as specified by (Becker and Ichino 2002). Additional propensity score model specifications were tested with little difference in results as suggested by (Dehejia 2005).

Table 2. Full Probit Regression of Hospital Closure

	Coefficient		SE
Ln of Medicare participants	0.438	***	0.128
Medicare participants making more than one visit	0.027		0.018
State political affiliation (Republican)	0.297	*	0.180
Unhealthy days	0.156	*	0.090
Smokers	-0.028	*	0.016
Obese	0.040		0.028
Binge drinkers	0.039	**	0.018
Diabetics	-0.013	**	0.007
Rural Urban Continuum Code	0.082	*	0.046
Discharges for ambulatory care	0.003		0.002
Black	-0.001	*	0.000
Log likelihood		-156.357	
Pseudo R^2		0.094	

Note: *, **, and *** indicate statistical significance at the p=0.10, p=0.05,and p=0.001 levels, respectively.
SE, standard error.

Table 3 displays the average treatment effects over the post closure time period of 2012-2014. The results are typically similar in their magnitude of the effect of a closure with varying degrees of significance. Negative differences indicate that the effect of a hospital closure for a treated group is smaller than that of a county that did not experience a closure when comparing to otherwise similar counties. The impacts on occupation and industry shifts are reported as percentage changes from 2012 to 2014. The nearest neighbor technique indicates that two of the outcome variables of interest are significant at the 10% confidence level or higher. Radius matching indicates that ten of the twenty-six outcome variables are significant at the 10% confidence level or higher. The paper finds that the negative impact of a hospital closure on poverty levels and unemployment are consistent with other papers on the topic when measured over the long term effect. Additionally, median rent values were found to decrease and the number of people working from home were found to be significant. Management, business, science, and arts occupations were significantly affected by hospital closures decreasing on average 1.634%. Construction, information, finance, and professional industries were also negatively impacted at a significant level. Kernel matching, which matches with more observations and weights them by similarity indicated that thirteen outcome variables were significant. The findings on general economic variables are once again consistent with previous work on the topic. Occupational changes indicated a decrease in management, business, science, and arts as well as sales and office occupations. Additionally, five industries were negatively impacted by rural hospital closures. Generally, the method of average treatment effects finds that a hospital closure will have a negative impact at the county level with decreases in economic measures and losses of jobs across various occupation and industry classifications.

Table 3. Average Treatment Effects Results

	Nearest Neighbor		Radius Matching		Kernel Matching	
Outcome Variable	Difference	t-stat	Difference	t-stat	Difference	t-stat
General Variables						
Poverty level (%)	2.748	1.58	4.952 ***	2.84	4.943 ***	3.45
Mean income	-921.727	-0.33	-3992.954	-1.58	-3954.602 ***	-3.19
Median income	-705.242	-0.61	-4185.239 ***	-2.96	-4146.909 ***	-2.32
Unemployment level	0.024	0.02	0.894 **	2.18	0.885 *	1.93
Mean travel time	1.385	1.28	0.270	0.36	0.253	0.25
Worked at home(%)	0.052	0.32	-0.265 *	-1.90	-0.262	-1.26
Median rent	-9.273	-0.30	-36.951 **	-2.18	-36.771 **	-1.87
Median home value	5042.424	1.02	-13700.000	-1.36	-13700.000 *	-1.99
Occupation (%)						
Management, business, science, and arts	-1.016	-1.02	-1.634 ***	-3.33	-1.616 **	-2.43
Service occupations	-0.117	-0.14	-0.372	-0.94	-0.367	-0.78
Sales and office occupations	-0.302	-0.51	-0.583	-1.53	-0.577 ***	-3.33
Natural resources, construction, and maintenance occupations	-0.108	-0.17	-0.134	-0.88	-0.133	-0.81
Production, transportation, and material moving occupations	-0.291	-0.67	-0.040	-0.13	-0.037	-0.06
Industry (%)						
Agriculture, forestry, fishing and hunting, and mining	-0.243	-0.26	-0.157	-0.43	-0.158	-0.70
Construction	0.191	0.74	-0.160 **	-2.07	-0.159	-0.70
Manufacturing	-0.111	-0.12	0.090	0.12	0.094	0.15
Wholesale trade	-0.045	-0.29	-0.060	-0.89	-0.059	-1.58
Retail trade	0.122	1.18	-0.167	-1.03	-0.164	-1.33
Transportation and warehousing, and utilities	0.086	0.59	-0.098	-1.43	-0.097 *	-1.66
Information	-0.219 ***	-4.46	-0.179 ***	-6.90	-0.178 ***	-5.71
Finance and insurance, and real estate and rental and leasing	-0.176	-1.27	-0.313 ***	-2.97	-0.313 ***	-2.56
Professional, scientific, management, waste management services	-0.242	-0.93	-0.536 ***	-4.60	-0.533 ***	-3.88
Educational services, and health care and social assistance	-1.082 *	-1.77	-0.593	-1.59	-0.584	-1.61
Arts, entertainment, recreation, accommodation and food services	-0.259	-0.49	-0.402	-1.24	-0.399 *	-1.85
Other services, except public administration	0.160	1.50	-0.070	-0.81	-0.068	-0.79
Public administration	-0.015	-0.04	-0.115	-0.65	-0.114	-1.43

Note: *, **, and *** indicate statistical significance at the p=0.10, p=0.05, and p=0.001 levels, respectively.

Difference in Differences

Similar to the average treatment effect results, the difference in difference model found a familiar negative impact of a hospital closure, but with varying levels of significance of the impact. Table 4 presents the full results of the difference in differences model with the three matching techniques. The economic measures of the county show a consistent negative impact of a closure to that of the average treatment effect. The changes in industry and occupation are similar to the average treatment effect results, but show less changes to be significant, with significant changes in wholesale trade; agriculture, forestry, fishing and hunting, and mining; information; and educational, and healthcare and social assistance industries. Comparing the results of the two methods simultaneously can lead to a greater understanding of the true impact, as well as provide direction for future research on the short term impacts of a closure. Examining the coefficients and signs of both the average treatment effect and the difference in differences methods results, it is found that the signs and magnitude of both methods are similar in outcomes. This can be interpreted to mean that the methods resulted in reliable outcomes, and can be deemed plausible as the true effect of a hospital closure (White and Lu 2010).

Table 4. Difference in Differences Results

	Nearest Neighbor		Radius Matching		Kernel Matching	
Outcome Variable	Difference	t-stat	Difference	t-stat	Difference	t-stat
General Variables						
Poverty level (%)	2.748	1.58	0.449	0.83	0.476	0.39
Mean income	-230.606	-0.55	-95.336	-0.26	-94.243	-0.69
Median income	-368.091	-0.79	-222.426	-1.22	-221.921	-1.49
Unemployment level	-0.085	-0.18	0.029	0.12	0.026	0.08
Mean travel time	-0.209	-0.58	-0.110	-0.67	-0.109	-0.78
Worked at home (%)	0.042	0.64	0.082	1.08	0.082 ***	4.12
Median rent	-14.697	-1.23	-10.335 **	-2.19	-10.309 ***	-3.20
Median home value	-796.970	-0.35	3.426	0.00	6.507	0.00
Occupation (%)						
Management, business, science, and arts	-0.214	-0.97	-0.177 **	-2.10	-0.176	-1.42
Service occupations	0.098	0.43	0.086	0.72	0.086	0.49
Sales and office occupations	-0.074	-1.03	-0.036	-0.35	-0.037	-0.32
Natural resources, construction, and maintenance occupations	-0.076	-0.82	-0.150	-1.22	-0.150 ***	-5.51
Production, transportation, and material moving occupations	-0.086	-0.48	-0.062	-0.76	-0.062	-0.89
Industry (%)						
Agriculture, forestry, fishing and hunting, and mining	-0.057	-0.58	-0.059 *	-1.74	-0.059	-1.47
Construction	-0.032	-0.36	-0.011	-0.16	-0.012	-0.22
Manufacturing	0.330	1.34	0.116	0.39	0.116	0.48
Wholesale trade	-0.038 *	-1.68	-0.000	-0.01	0.000	0.00
Retail trade	-0.092	-0.53	-0.098	-1.16	-0.098	-1.09
Transportation and warehousing, and utilities	0.021	0.28	0.028	0.92	0.028	1.27
Information	-0.047	-0.89	-0.029 *	-1.68	-0.029	-0.86
Finance and insurance, and real estate and rental and leasing	0.003	0.06	-0.000	-0.00	-0.000	-0.00
Professional, scientific, management, waste management services	-0.075	-0.47	-0.038	-0.59	-0.037	-0.36
Educational services, and health care and social assistance	-0.215	-0.90	-0.177 ***	-2.26	-0.177 *	-1.78
Arts, entertainment, recreation, accommodation, food services	-0.123	-0.61	-0.035	-0.63	-0.036	-0.83
Other services, except public administration	0.046	0.72	0.021	0.32	0.022	0.30
Public administration	-0.072	-1.04	-0.057	-1.99	-0.057	-0.96

Note: *, **, and *** indicate statistical significance at the p=0.10, p=0.05, and p=0.001 levels, respectively.

Conclusions

Two main findings dominate this study's results in examining the relationship of the short term economic impact and rural hospital closures. The first is that the short term impacts are similar to that of the long term found in other studies. A hospital closure will negatively impact the economic measures of a community over the short term, affecting a range of issues including poverty level, income, unemployment, and home values. The second is that with the loss of a hospital, employment is not only affected in the healthcare industry, but other industries and occupations experience a decrease in the number of jobs as well. Furthermore, this study exemplifies the notion that the effect of closure can be expected shortly after a closing, adding to the previous work of the impacts in the long term.

Generally, the paper documents that in the short run a hospital closure negatively impacts a county on various levels. Documenting this impact will be important in the future as budgets become tighter and communities will have to work hard to present the case for continuing hospital funding in rural areas. Notably by making statements on the causality of the relationship, (as the paper attempts to do) will help in building strong cases for a continued or increased funding.

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