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Long-Term Economic Impacts of USDA Water and Sewer Infrastructure Investments in Oklahoma

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One of the U.S. Department of Agriculture Rural Development's most popular programs is the funding for public water and sewer infrastructure projects in rural communities. This article reviews the water and sewer infrastructure projects funded in the state of Oklahoma between 1990 and 2000 and evaluates their impact on different measures of economic growth over both the short (one to 10 years) and long (10 to 20 years) term. Evaluation techniques include multivariate regression and average treatment effects. Results suggest that although most economic growth measures (population, income levels, and poverty levels) are not impacted by the program, housing values do show a statistically significant increase in communities receiving water or sewer infrastructure funding over the long term.

Key Words: average treatment effects, economic growth, public water infrastructure, rural development

JEL Classifications: H76, O18, R11, R58

For a number of decades, the U.S. Department of Agriculture (USDA) has implemented a broad mix of support programs aimed at the development of rural America. Many of these efforts are heavily focused on providing infrastructure to rural areas with distinct programs to assist in building rural housing, develop high-speed telecommunications networks, or aid in the construction of public water/sewer utilities. The ultimate goal of these programs is to combat factors that continue to plague rural areas such as poverty and unemployment, population decline, and the isolation of rural residents. Thus, an underlying assumption of these USDA Rural Development (RD) programs is that the provision of infrastructure will have positive economic impacts on the rural areas in which they are implemented over either the short term (defined in this article as zero to 10 years) or the long term (10 to 20 years).

The economic literature typically defines infrastructure as large, capital intensive natural monopolies such as highways and other transportation facilities, natural gas distribution, water and sewer lines, mass transit, and communications systems with the majority of them publicly owned (e.g., Joskow, 2006; Pindyck and Rubinfield, 1995). Natural monopolies typically occur when the economies of scale for a given industry are so large that one firm supplying the whole market with services will be

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the most efficient option.[1] This is the case with water distribution and sewer services, which are generally thought to have characteristics of natural monopolies. For example, this article looks at communities that have received USDA RD funding for water and sewer services. The recipients of these USDA RD funds are public water utility companies, which are the single water suppliers for particular rural water districts in Oklahoma.[2] Furthermore, most of the funding for this publicly owned infrastructure comes from state and local government sources as opposed to federal funds. Combined with the fact that investments in infrastructure are often highly visible to the general public, state and local policymakers have historically been very interested in providing public infrastructure to support regional economic development.

Infrastructure capital is just like any other capital in that it is purchased on the market at the time when construction or installation takes place; however, it is rarely ever sold. This lack of sale is the reason why economic rates of public infrastructure depreciation are almost never directly measured (Gramlich, 1994). With shrinking government budgets and a need to demonstrate program effectiveness, programs that invest heavily in public infrastructure must develop ways of documenting their contributions. The economic literature clearly recognizes that providing infrastructure by itself creates a short-term economic impact as construction and related spending take place. However, empirical investigation into the long-term economic impact of such investments, particularly in rural areas, is lacking.

Therefore, an overarching question for the USDA RD program is whether investments in rural infrastructure have short- or long-term economic impacts on rural communities. In particular, do these investments impact population growth, poverty levels, income measures, or housing values among the rural residents who receive them? We attempt to answer this question using community-level data from a single state (Oklahoma) and information about which communities received funding from one particular USDA infrastructure (water and sewer) program during the period 1990–2000. Two distinct econometric techniques are used to assess whether receiving funding impacted a variety of economic growth measures over both the short (less than 10 years) and long (10 to 20 years) terms. The goals of this study are to 1) determine whether economic growth has occurred in the areas that receive RD water and sewer infrastructure funding; 2) uncover the short-term and long-term relationships between water and sewer infrastructure program investment and different measures of economic growth; and 3) identify whether the water and sewer infrastructure projects implemented actually caused different types of economic growth over the short term and the long term.

Simple descriptive statistics and t-tests on eight different economic growth measures between communities that received/did not receive water and sewer infrastructure funding are used to assess goal (1). Multivariate regression analysis is used for goal (2), with eight economic growth measures as dependent variables and a host of potentially influential independent variables that includes a dummy variable for being a recipient of a RD water/sewer infrastructure project. This technique allows for identification of whether the RD projects significantly impacted economic growth after controlling for other observable characteristics and over what timeframe these impacts are observed. Goal (3) requires that we move beyond regression to identify whether the water/sewer infrastructure projects implemented are the cause of the growth. To assess causality, a semiparametric technique known as the average treatment effect method is used. This technique involves incorporating a propensity score-matching procedure that looks at differences in the growth rates between places where funding was provided and places with similar characteristics where no funding was provided.

The literature review that follows this introduction demonstrates that only a limited number of studies have focused on the economic impact of public infrastructure in rural areas

[1] Economies of scale are defined as cost advantages that an enterprise obtains as a result of expansion.

[2] http://www.owrb.ok.gov/maps/maps2/ruralwater.php

and no studies that we are aware of use multiple econometric techniques to test the robustness of their findings. The methodology and data used for the study are then presented, including basic descriptive statistics. The results of the two econometric techniques are reviewed and compared, and the article concludes with a discussion of policy implications.

Literature Review

The importance of infrastructure to the growth and functioning of an economy is recognized in a wide variety of empirical research, which suggests that infrastructure is fundamental to economic development. Regions that lead in economic development usually have better physical infrastructure. This relationship drives infrastructure development and special needs programs[3] to account for more than 90% of the rural development funding provided by the USDA (Blanford, Boisvert, and Davidova, 2008). However, not all research in this field has demonstrated that investment in public infrastructure has resulted in economic growth. Table 1 provides a summary of previous studies on whether infrastructure impacts economic growth, including those that find a positive impact on growth and others that find only a small or negative impact. The studies in Table 1 that find a positive impact generally hypothesize that public infrastructure stimulates economic activity in two primary ways: by increasing the productivity of private firms or as an unpaid factor of production. Private inputs are typically purchased in a free market; however, public capital is provided by government and financed through taxes. Because tax payments are not necessarily connected to the quantity of public capital used by private firms, public capital can be seen as an unpaid input to the firm's production process. Aschauer (1989) argues that public investment creates an increase in the rate of return to private capital, resulting in private investments four to seven times as large as the original public investments themselves.

Various studies in Table 1 attempt to define the extent to which public infrastructure investment can induce excess aggregate demand, stimulate production in various industries, or impact per-capita income. Aschauer (1989) finds that "core" infrastructure (streets and highways, airports, electrical and gas facilities, mass transit, water systems, and sewers) possesses the greatest explanatory power for increased productivity and raises private investment and value added in sectors that directly benefit from public capital investments such as transportation. The types of infrastructure found to be the most responsible for improving productivity are highways, widened or expanded roads, and improved water treatment and sewer plants. Therefore, if a local or state government provides these necessary facilities, private firms do not need to construct their own. In this way, infrastructure can be viewed as a direct input into a firm's production process (Duffy-Deno and Eberts, 1991; Eberts, 1990). Similarly, Fox and Porca (2001) summarize existing research on this topic and note that providing water, electricity, and telecommunications is of paramount importance to business development. They also suggest that public infrastructure investment has a positive effect on entrepreneurship and company-level decisions on where to locate; both are important measurements of economic development. Looking specifically at rural areas, Fox and Porca (2001) detail the conceptual relationship between infrastructure and economic growth, listing several ways that rural economies could benefit from improved infrastructure (improving productivity of existing business, attraction of other productive inputs, providing an attractive environment that might compensate for lower wages). Fox and Porca also note, however, that although infrastructure is essential to accommodating growth, it is not a sufficient condition for stimulating self-sustaining growth that would not occur in the first place. Nevertheless, Deno (1988) finds that public investments in highways and water/sewer public infrastructure have a strong positive effect on firm-level manufacturing output and that water/sewer

[3] Special needs programs are defined by the USDA as those designed to provide individuals and communities with some level of basic services such as housing, sanitation, or health care.

Table 1. Previous Studies on Infrastructure and Economic Growth

Study	Type of Infrastructure	Areas of Focus	Dependent Variable	Significant Results/Findings
Studies that found a positive impact				
Aschauer (1989)	Public capital investments	Metro and nonmetro	Output per unit capital and total factor productivity of nonmilitary public capital stock	Increase in public capital investments of $1 billion would result in anywhere from $1 to $1.5 billion in private investments
Eberts (1990)	Roads, streets, bridges, water treatment and distribution systems, irrigation, waterways, airports, and mass transit	Metro	Summarized findings from previous research	Public capital stock makes a positive and statistically significant contribution to manufacturing output
Deno (1988)	Highway, sewer and water public investments	Metro	Profit function of: 1) public capital stock in roads, highways and bridges; 2) storm sewers and sewage facilities; 3) water supply and treatment	Highway, sewer and water public investments have a strong positive effect on the supply side of the firm's manufacturing output; water and sewers have the largest effect in expanding regional, highways have the largest effect in declining regions
Bagi (2002)	Water and sewer investments	Metro and nonmetro	Descriptive statistics on employment, income, property tax base, private and public investments	1) Rural and urban water/ sewer projects both generate much greater economic benefits than their total construction cost; 2) create additional jobs, generate private investment, attract additional government funds, and increase the property tax base; 3) most urban projects experienced larger economic impacts than rural projects

Table 1. Continued

Study	Type of Infrastructure	Areas of Focus	Dependent Variable	Significant Results/Findings
Duffy-Deno and Eberts (1991)	1) Sanitary and storm sewers and sewage disposal facilities; 2) roadways, sidewalks, bridges, and tunnels; 3) water supply and distribution systems; 4) public hospitals; and 5) public service enterprises—airports and seaports	Metro	Per-capita income; intergovernmental revenue; property tax rate; state tax liability; percentage of owner occupant housing; percentage of population below poverty line	Positive and statistically significant effects on per-capita personal income
Studies that found small or negative impact				
Evans and Karras (1994)	Government capital and services	Metro and nonmetro	Gross state product in all private nonagricultural industries	1) Fairly strong evidence that government educational services are productive; 2) no evidence that other government activities are productive; 3) productivity of government capital is significantly negative
Holtz-Eakin (1994)	Public capital stock (roads, bridges, water-supply systems, sewerage facilities, etc.)	Metro and nonmetro	1) Private output; 2) private employment; 3) private capital; 4) public capital	The use of aggregated data did not reveal significant linkages between the provision of infrastructure and increase in private productivity
Holtz-Eakin and Schwartz (1995b)	Public infrastructure capital	Metro and nonmetro	Productivity growth	Infrastructure investment has a negligible impact on annual productivity growth between 1971 and 1986
Holtz-Eakin and Lovely (1996)	Public infrastructure capital	Metro and nonmetro	Productivity effects	Indicate little contribution of public infrastructure to direct output in all sectors, except in the manufacturing

and highway infrastructures also have a strong complementary relationship with private labor and capital in areas with declining economic growth. Probably the most in-depth research regarding the economic impact of rural water and sewage investments is performed by Bagi (2002). He examines the impact of 87 water and sewer projects across 30 different states with 54 of them located in urban areas and 33 in rural areas. All of the projects were financed by the Economic Development Administration (EDA) and built for specific firms or potential investors. Each grant recipient was asked to have local economic developers and other officials estimate the impact of the EDA-funded projects. Indirect benefits were seen in the potential to attract new businesses that would tap into the new water/sewage lines and retail stores/other services that would emerge as a result of increased economic activity, population, and personal and family income. Results of the study reveal that these investments can save and create additional jobs, stimulate private sector investment, attract additional government funds, and increase the property tax base. He arrives at the conclusion that urban water/sewer projects experience as much as two to three times more of an economic impact than projects taking place in rural areas, basically as a result of the remoteness and small size of the rural communities. Similarly, Webber (2010) suggests that productivity growth and its spillover effects are directly influenced by location remoteness and accessibility. Firm agglomeration has huge positive effects on productivity; however, this type of clustering is rare in rural areas. Webber's analysis is theoretical and has little empirical backing.

Deno and Bagi's findings are complementary to an early study by Borcherding and Deacon (1972) that uncovered large and statistically significant income elasticities for highway and public water/sewer expenditures on payroll. The studies discussed so far displayed findings that support the concept that public infrastructure investments are responsible for increased economic growth, productivity, and employment. However, in a series of papers in which various econometric assumptions are challenged and criticized, some authors find little evidence of positive spillover effects from public investments. Evans and Karras (1994) argue that besides public educational services, no other government activities have any positive impact on state-level productivity. Instead, the evidence they have found is negative and usually with high significance. Holtz-Eakin (1994) argues that once controls are in place for state-specific effects, the elasticity of output and productivity in private firms with respect to public infrastructure is zero. Holtz-Eakin and Schwartz (1995a) further state that the link between infrastructure and productivity growth is controversial and express their surprise that infrastructure research has developed in isolation from the large literature on economic growth. They find little support for claims of a dramatic productivity boost from increased infrastructure investments or spillovers (Holtz-Eakin and Schwartz, 1995b). These estimates are in direct contrast to the productivity effects found by other researchers, especially Aschauer. Finally, Holtz-Eakin and Lovely (1996) find that public infrastructure investments only increase direct output in the manufacturing sector with little contribution to other sectors. Rodriguez (2010) provides a nice summary of these and other important papers in the literature and concludes that "on balance, the research is either far from conclusive or suggests that infrastructure investment does improve rates of growth" (p. 13).

Table 1 suggests that the research evidence on whether infrastructure induces growth or growth influences infrastructure has been mixed. Although many studies have found economic growth positively affected by public infrastructure provision, others have found limited evidence of productivity. This article adds to the literature by focusing on an infrastructure program specifically for rural communities, considering community-level economic outcomes (as opposed to private firm productivity) and looking distinctly at short- versus long-term impacts.

Methods and Procedures

This research will attempt to answer the question of whether the Oklahoma communities that obtained USDA RD investments in public water and sewer infrastructure over the period 1990–2000 experienced short- or long-term economic growth. Two different econometric techniques: 1) multivariate regression analysis and 2) the average treatment effects method incorporating propensity score matching are used.[4] The two methods are distinct in their assumptions; comparing the two results will offer a way to test the robustness of the findings.

Ordinary Least Squares Regression

Identifying the economic impact created by the newly provided infrastructure poses several challenges that must be addressed. Infrastructure itself cannot create economic growth and sustained job creation. Instead, it can only create temporary jobs associated with construction or maintenance of the infrastructure (that are typically captured by multiplier-oriented economic impact studies). Predicting how specific types of infrastructure will be used by various industries is extremely difficult. Having this in mind, economists often estimate the economic impacts of infrastructure by using a modified growth model. The growth model is a methodology to predict a region's growth over time (Lehr et al., 2005; Shideler, Badasyan, and Taylor, 2007). This model predicts the economic growth of a region during one period based on the level of economic activity of some previous period plus any compounded growth that would be expected to occur between the two periods. Mathematically, this process can be expressed as:

$$(1) \qquad Y_t = AY_{t-i}^{\alpha}\, e^{\mathrm{ri}}$$

where: Y_t represents the economic level at time t,

A is a constant,

α is a scaling parameter, and

e^{ri} is the formula for compounded growth at rate r for i periods.

[4] A reviewer notes that a difference-in-difference approach might also be an appropriate methodology for comparing counterfactuals. We focus on propensity score matching because our model relating to the required "common trend" between control and treatment groups includes a large number of observables. The difference-in-difference approach may be more applicable if the common trend is highly influenced by unobservables (Abadie, 2005).

The most important element in this approach is to determine the correct expected growth rate, r, between the two periods. Because of the importance of this step, the growth rate, r, is determined statistically using multivariate regression analysis. Transforming this growth equation using natural logarithms, assuming that A and α equal one (which are standard assumptions when empirically testing growth models), and defining time periods in such a way as to make i = 1, we derive the following equation:

$$(2) \qquad \ln\left(\frac{Y_t}{Y_{t-1}}\right) = r_t = \beta_1 X_{1t} + \ldots + \beta_n X_{nt} + \gamma I_t + \varepsilon_t$$

Equation (2) states that the economic growth rate r_t for a community is a function of the explanatory variables (X_{1t} through X_{nt}), an infrastructure dummy variable, I_t, their respective parameters β and γ, and an error term ε. In this study, the dependent variable (Y) represents eight distinct measures of economic growth, the explanatory variables (X) include a variety of socioeconomic factors, and the error term ε is assumed to have a log-normal distribution. The infrastructure dummy variable (I_t) is created by assigning a one to all communities that received public funding for the program of interest and zero otherwise. In particular, we are interested in whether the infrastructure investments impacted growth or whether $\gamma = 0$. Each of the eight dependent variables is regressed following the model stated. The findings from two time periods are compared: the short term (less than 10 years after implementation) and the long term (10 to 20 years after implementation).

Average Treatment Effects

Previous research has shown that regression analysis can verify whether infrastructure investments are correlated with the measures of economic growth, but it cannot establish a firm causation. One increasingly popular method to address this problem is to use matching techniques because they are model-unbiased and hence do not contribute to drawing restrictive assumptions associated with ordinary least squares (OLS) (Imbens, 2004). Therefore, the average treatment effect (ATE) method is often used as a way to compare treatments (or interventions) in randomized experiments, evaluation, or policy interventions. The ATE measures the average causal difference in outcomes under the treatment and under the control. In a randomized trial or an experiment, the average treatment effect can be estimated using a comparison in means between treated communities (those that received public infrastructure funding) and untreated communities (those that did not) for some prespecified time period after implementation. This is the "treatment effect" because those areas with publicly funded water/sewer infrastructure are considered to have been "treated." Therefore, we let ΔY_{t1} and ΔY_{t0} be the change in economic indicators of the areas between time *t* and *t-1* with and without public water/sewer infrastructure provided, respectively. The ATE can be represented as:

$$(3) \qquad ATE = E(\Delta Y_{t1}|I_t = 1) - E(\Delta Y_{t0}|I_t = 1)$$

where I_t equals one for areas receiving infrastructure funding (treated) and zero for areas not receiving funding (nontreated). However, we can observe either ΔY_{t1} or ΔY_{t0} for a particular place, but not both, because each community has either participated or not participated in the USDA water-supply and sewage systems infrastructure program. In reality, the second expected value in equation (3) is not observable because communities without any infrastructure investments will (by definition) not have been "treated." Thus, each "treated" community needs a comparable, nontreated counterpart. To accomplish this (and estimate the second expected value in equation [3]), we need to "match" communities that obtained the investment with otherwise similar communities that did not receive any funding. The first step in doing so is to estimate the propensity score, that is, the likelihood of obtaining an infrastructure project. Most applications in the statistics literature use a logit model to estimate this propensity score, where the conditional probability of obtaining an infrastructure project is modeled on observable predictors such as the socioeconomic variables included in the OLS regressions. The propensity score is then used to match treated and nontreated communities by creating blocks of communities with similar propensity scores. A test developed by Becker and Ichino (2002) is used to determine whether the treated and nontreated communities in each block have the same distribution of covariates, essentially ensuring that the matches are in fact "good." The literature suggests various methods for matching, and we use both nearest neighbor matching and kernel matching techniques, developed by Becker and Ichino (2002) and Dehejia and Wahba (2002) to test the robustness of our results. The nearest neighbor technique matches treated and nontreated units by searching for the closest propensity score between the two groups. At times, however, the difference in these propensity scores may be large. Kernel matching seeks to solve this problem by weighting the difference between propensity scores in a group and matching each treated unit with a weighted counterpart from the nontreated group.

Data

Data on the existence of water/sewer infrastructure projects in Oklahoma during the period of 1990–2000 was provided by the state USDA RD office. Project funds (both grants and loans, with approximately a 30–70 ratio) are limited to communities of less than 10,000 population, and communities must be denied credit through normal commercial banks to be eligible. Each project has been manually linked to a community in Oklahoma along with the amount of funding (broken out by grant and loan totals) and year of commitment. A total of 143 community-level water/sewer infrastructure projects are included in the study, located in a wide variety of communities across the state (Figure 1).

Data on community-level economic and socioeconomic measures come from the U.S. Census Bureau's data series from Census 1990, Census 2000, and estimates from American Community Survey (ACS) 2005–2009. After eliminating communities that did not exist in every time period, 564 places were included in the final data set. Ideally, we would like to have

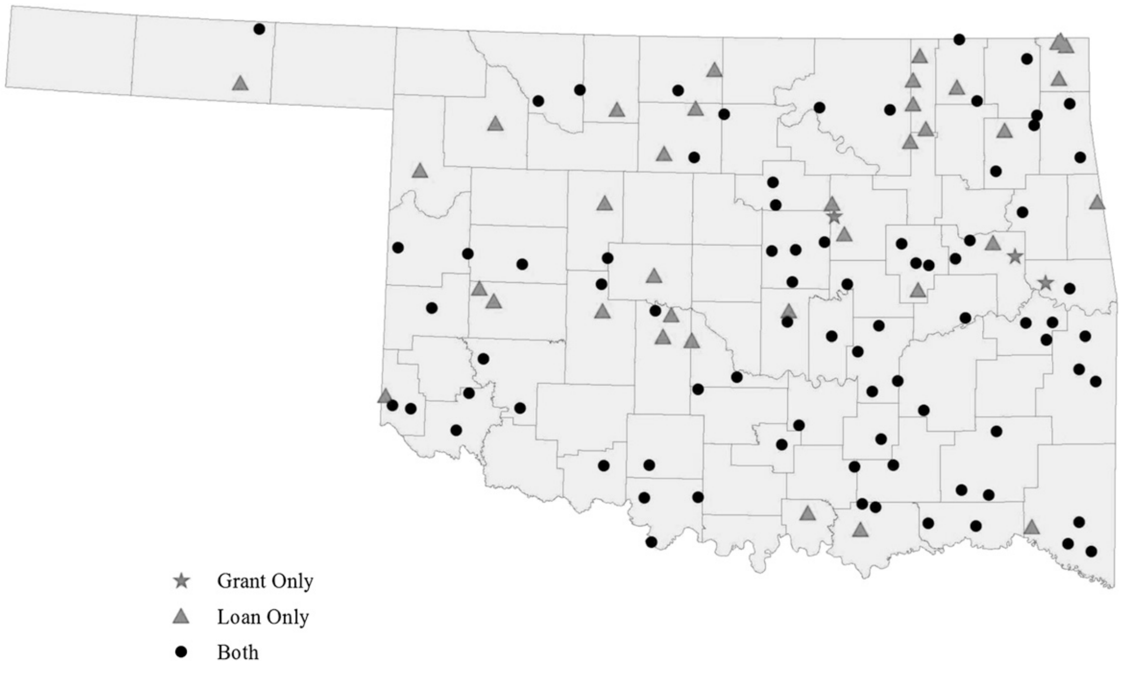

Figure 1. USDA Rural Development Water/Sewer Infrastructure Grants and Loans in Oklahoma, 1990–2000

data for each community on an annual basis, which would enable pre/post comparisons over very specific time periods. However, community-level data are only available for the Census and the five-year ACS, and the ACS was not available during the 1990s. As such, the beginning and end points of our analysis are the same, although communities received grants/loans at various points during the 1990s.[5] The data do indicate that the majority of the loans took place before 1995, suggesting that in most instances, at least five years passed before the short-term impacts are evaluated.

Because the goal of RD programming is to improve economic conditions in rural areas, we use measures of general economic development in our data set (as opposed to other types of private productivity measures listed in Table 1). The data set includes the following dependent variables, each at the city level: 1) population; 2) median household income; 3) per-capita income; 4) percent of households with earnings; 5) percent of households with self-employment income; 6) percent of population living in poverty; 7) percent of vacant housing units; and 8) median housing value. Growth rates for the economic indicator variables are created for both the short (1990–2000) and long (ACS, 2009) terms.[6] The mean values for these growth rates, broken into categories for cities that received/did not receive funding, are shown in Table 2.

Data for the explanatory variables include the following socioeconomic factors: 1) racial/ethnic characteristics of the population; 2) education levels (percent of population with Bachelor's degrees); 3) percentage of population with mean travel time to work under 15 minutes; 4) percentage of population included in the labor

[5] Other studies evaluating USDA programs have followed this same approach despite program awards being made in several years, notably Kandilov and Renkow (2010).

[6] As a reviewer points out, differences do exist in the sampling methods of the ACS versus the decennial census. However, the Census Bureau web site indicates that it is acceptable to compare ACS 5-year estimates with Census 2000 data for the tables that contain these dependent variables.

Table 2. Dependent Variable Summary Statistics: Mean Cumulative Growth Rates in Percent (Treated = Received Funding)

		Growth Rates 1990–2000			Growth Rates 1990–ACS2009		
Name	Dependent Variable Description	Not Treated	Treated		Not Treated	Treated	
POP	Population (ln)	7.1	8.7		9.9	10.4	
MHI	Median household income (ln)	56.4	62.4		103.8	108.9	
PCI	Per-capita income (ln)	61.1	62.1		112.6	105.6	
HHE	% of households with earnings	2.3	5.0	**	2.3	6.7	**
HHSEI	% of households with self-employment income	–3.6	13.6		–17.6	–16.5	
POV	% in poverty under 1.00	0.4	–15.7		6.3	–2.6	
VHU	% vacant housing units	–13.6	–9.1		13.9	24.9	
MHV	Median house value (ln)	45.8	48.1		117.2	131.9	**

Note: ** indicates that the means are statistically significantly different at the $p = 0.05$ level.

force; 5) percentage of households lacking complete plumbing facilities; 6) median year of structures built; 7) population density, and 8) Rural–Urban Commuting Area (RUCA) codes.[7] The average values for these independent variables, broken into categories for cities that received/did not receive funding for the years between 1990 and 2000, are shown in Table 3.

Simple t-tests of the mean growth rates (Table 2) demonstrate that most of the economic growth measures do not statistically differ between communities that received or did not receive water or sewer infrastructure funding. Although the numbers show that places with water/sewer infrastructure investments typically experienced greater growth for nearly all examined measures, widely fluctuating standard errors on these estimates lead to only a few variables demonstrating significantly different means. Table 2 reveals that the growth rate in the percentage of households with earnings is significantly higher for treated communities over both the short and long terms. Similarly, median house values increased by 131.9% in communities that received a water/sewer project over the long term, which is statistically higher than the 117.2% increase seen in communities without a project. Thus, we can say that at least some type of economic growth has occurred in communities that received this type of infrastructure funding.

However, simple t-tests do not allow us to single out the impact of infrastructure, and they do not lead to statements about causality. For these results, we turn to regression analysis and average treatment effects.

Results

Ordinary Least Squares Regression Results

Table 4 provides the results of the eight regression models as laid out in equation (2). Each equation includes a series of control variables listed in Table 3. In particular, each model not only includes the socioeconomic variables described, but also lagged (1990) values of the other dependent variables shown in Table 2. For example, the equation for population growth includes 1990 values of per-capita income, households with earnings, households with self-employment income, vacant housing units, households in poverty, median house values, and also original (1990) population levels as control variables. However, as several recent studies have noted (Brown, Lambert, and Florax,

[7] The RUCA codes are designed for measuring rurality at the census tract or zip code level. They capture community size as well as primary commuting flows to urban areas and urban clusters, and they are based on 1990 Census work commuting information. We map the zip code data to communities in our data set with all of our rural communities having a single zip code. The RUCA codes range from 1 to 10.6 with 10.6 being the most rural.

Table 3. Independent Variable Summary Statistics, 1990 and 2000: Means (Treated = Received Funding)

Independent variable	1990 Not Treated	1990 Treated	2000 Not Treated	2000 Treated
% black population	3.74	6.07	3.73	5.44
% other race population	10.25	10.94	10.07	11.03
% population with Bachelor's degree	6.13	5.83	8.09	7.32
% of population with mean travel time to work <15 minutes	37.65	43.89	33.31	39.27
% of population included in the labor force	55.58	53.26	57.02	55.01
% of households lacking complete plumbing facilities	1.86	1.45	2.72	2.22
Median year structure built	1962	1962	1964	1963
Population density (people per square mile)	840.60	896.10	804.90	828.10
Unemployment rate	5.60	6.12	3.30	3.60
Rural–Urban Commuting Area Codes	6.60	7.04	6.37	7.04

Note: None of the differences in mean values between treated/not treated are statistically different from zero in 1990 or 2000.

2013; Lambert, Xu, and Florax, 2013), the inclusion of lagged dependent variables on the right hand side of an adjustment model such as the one used here can potentially result in issues with endogeneity. In particular, Griliches (1967) originally noted that as growth processes (including the process represented by equation [2] of this article) progress toward equilibrium, including a lagged outcome variable in such an equation would result in endogeneity as a result of the correlation between this earlier-term variable and the current-period error term. To ease these concerns, we also run the models without the lagged dependent variable as an explanatory variable and get consistent results in all models for our parameter of interest (γ).

Thus, each equation controls for a host of other factors that might also influence growth rates in the variable being described, hopefully allowing for isolation of the impact from the water/sewer infrastructure program. Note that Table 4 only reports the coefficients and t-values associated with the infrastructure dummy variable for the sake of brevity. Generally speaking, however, the coefficients associated with other variables in the analysis are consistent with previous studies using similar dependent variables such as positive impacts of higher education or negative impacts of more people living in poverty. The R^2 values range from 0.12 to 0.50, which are reasonable results for cross-sectional data that include growth over time (Czernich et al., 2011; Faini, Annez, and Taylor, 1984). The full results of all eight OLS models are included in Appendix A.

Table 4 suggests that most growth rates in various economic measures are not impacted by participation in the infrastructure projects. In particular, no short-term parameter estimates on the infrastructure variable are statistically significant, and only one long-term coefficient is significant: the coefficient associated with median house value. Interpreting this coefficient suggests that communities that participated in infrastructure projects had 5.0% higher growth in their median house values than did otherwise similar nonparticipating communities. When lagged dependent variables are excluded, this same pattern holds: the only statistically significant relationship for the infrastructure dummy is with long-term median house values, this time suggesting increases of 7.0% for communities that participated in infrastructure projects.

Of importance to note is that the coefficients included in Table 4 deal specifically with dummy variables for the implementation of any type of water/sewer program in the community. We separately ran regressions on dummies for programs funded only by loans or grants with findings similar to those in Table 4. We also ran a host of regressions using the dollar value of the grants and loans as opposed to simple

Table 4. Ordinary Least Squares Results: Significance of the Infrastructure Funding Dummy Variable

	Short term (1990–2000)			Long term (1990–ACS2009)			
Dependent Variable	Coefficient	t-value	R^2	Coefficient		t-value	R^2
POP	0.02	0.91	0.12	0.05		1.27	0.17
MHI	–0.01	–0.24	0.47	–0.01		–0.47	0.29
PCI	–0.02	–1.20	0.37	–0.02		–0.94	0.25
HHE	0.01	–0.53	0.50	0.02		0.32	0.18
HHSEI	0.03	0.64	0.33	0.02		0.39	0.25
POV	–0.01	–0.67	0.29	0.06		0.53	0.25
VHU	–0.01	–0.26	0.33	0.06		0.61	0.30
MHV	–0.01	–0.58	0.17	0.05	*	1.72	0.19

Note: * indicates statistical significance at the $p = 0.10$ level.
POP = Population; MHI = Median Household Income; PCI = Per Capita Income; HHE = Percentage of Households with Earnings; HHSEI = Percentage of Households with Self-employment Income; POV = Percentage of Individuals in Poverty; VHU = Percentage of Vacant Housing Units; MHV = Median House Value.

dummy variables but did not obtain any significant short- or long-term impacts.

Multivariate regression, however, allows for only limited claims about causality and further requires specific assumptions regarding distributions, heteroscedasticity, and misspecification. Diagnostic tests show that there are no collinearity issues, because all variation inflation factors are within the acceptable bounds.[8] A battery of specification tests regarding normality of the residuals, heteroscedasticity, and omitted variables on our OLS assumptions reveal that there were initially some issues with several of these assumptions, including problems with heteroscedasticity and omitted variables. Because normality is not required to obtain unbiased estimates of the regression coefficients, we concentrate on correcting other problems in our models. We were able to overcome the heteroscedasticity problems and obtain the Huber/White corrected robust variance estimates by running a robust regression on all models that showed problems with heteroscedasticity (through the Breusch-Pagan test). The Ramsey-Regression Specification Error Test test[9] reported issues with omitted variables in our models, which was difficult to correct for because only a limited number and type of variables existed in our data set. Attempts to control for these issues by varying the amount and typology of the control variables result in the coefficients displayed in Table 4; however, they (along with the potential endogeneity issue) still lead to questions regarding the robustness of these outcomes. Thus, we turn to the average treatment effect methodology to see if it helps to confirm or refute our OLS findings.

Average Treatment Effect Results

To generate propensity scores for Oklahoma communities, the likelihood of receiving water/sewer infrastructure funding is modeled by logistic regression. Independent variables include 1990 versions of the characteristics shown in Table 3 along with 1990 values for per-capita income, households with earnings, households in poverty, vacant housing units, and population. RUCA codes from 1990 are also included when estimating propensity scores. The final specification used has a pseudo R^2 of 0.09 and satisfies the Becker and Ichino (2002) test regarding distribution of covariates between treated and nontreated groups. The results of this specification

[8] Variation inflation factors (VIFs) attempt to quantify the severity of collinearity in OLS regressions. Conventional cutoffs for VIFs that might indicate collinearity problems occur when their values are higher than five to 10 (Stine, 1995); the averages for our eight OLS regressions range only from 2.06 to 2.20.

[9] With quadratic specifications or natural log for growth.

Table 5. Average Treatment Effects Results

	Short Term (1990–2000)				Long Term (1990–ACS2009)				
	Nearest Neighbor		Kernel Matching		Nearest Neighbor		Kernel Matching		
Dependent Variable	Difference	T-stat	Difference	T-stat	Difference	T-stat	Difference		T-stat
POP	0.04	0.87	0.04	0.88	0.05	0.92	0.03		0.55
MHI	–0.06	–1.19	–0.06	–1.51	–0.05	–0.65	–0.07		–0.93
PCI	0.00	0.06	0.01	0.09	0.03	0.42	–0.01		–0.20
HHE	–0.02	–1.22	–1.01	–0.81	0.01	0.11	0.01		0.24
HHSEI	0.03	0.25	0.06	0.49	–0.08	–0.85	–0.17		–1.45
POV	–0.09	–0.86	–0.08	–0.93	–0.04	–0.38	–0.05		–0.46
VHU	0.01	0.16	–0.01	–0.16	0.08	1.13	0.01		0.18
MHV	–0.02	–0.46	–0.04	–0.92	0.10	1.31	0.13	*	1.74

Note: * indicates statistical significance at the $p = 0.10$ level.
POP, population; MHI, median household income; PCI, per-capita income; HHE, percentage of households with earnings; HHSEI, percentage of households with self-employment income; POV, percentage of individuals in poverty; VHU, percentage of vacant housing units; MHV, median house value.

are shown in Appendix B. Additional propensity score specifications were tested with little difference in the results.[10]

Table 5 displays the results of the average treatment effect methodology for the eight dependent variables over the two time periods in question. The difference between treated and nontreated groups is observed using both the nearest neighbor and kernel matching techniques in each time period, typically with similar quantitative results. Positive differences indicate that the growth rate for the treated group is higher than the growth rate for the nontreated group.

Similar to the OLS results, only a single impact is identified using the ATE approach. The kernel matching technique identifies a 13.1 percentage point difference in the growth rates of median household values for communities that obtained an infrastructure project, a result that is significant at the 10% confidence level. This impact occurs only over the long term and is somewhat consistent with the 5.0 percentage point difference identified using multivariate regression. No other significant findings are uncovered with either the nearest neighbor or kernel matching methods.

[10] This strategy is suggested by Dehejia (2005) who notes that, "one must examine sensitivity of the estimate to small changes in the specification" (p. 363) when applying propensity score methods.

Conclusion

Two main findings dominate this study's effort to uncover the relationship between participation in the USDA RD water/sewer infrastructure program and various measures of economic growth. The first is that no short-term (less than 10 years) impacts are documented, regardless of the econometric technique used. The second is that over the long term (10 to 20 years), only growth rates in median house value demonstrate a positive response to infrastructure program participation using both OLS and average treatment effect methods. Quantitatively, communities that obtain a water infrastructure project can expect their median house values to increase by between five and 13 percentage points higher than in an otherwise similar community without a water infrastructure project.

In particular, the ATE results allow for the claim to be made that increased growth in median house values in Oklahoma communities that received USDA infrastructure funding is mainly caused by these investments. However, the program cannot make similar claims about other community economic variables of interest such as median household income, population, or poverty levels.

From a policy standpoint, the first finding suggests that infrastructure programs should not expect a quick turnaround on their investment.

Furthermore, the fact that only one long-term impact is robustly documented in this study does not necessarily suggest that the USDA water and sewer infrastructure program is misguided or is spending money inappropriately. As the requirements for the program suggest, communities that apply are generally small and have limited options for improving their infrastructure. At a minimum, however, this analysis should lead policymakers to question what type of an impact they expect similar types of programs to have and over what timeframe this impact is expected to be shown. Of course, infrastructure improvements are likely to have impacts on difficult-to-quantify concepts such as resident quality of life. Many good reasons exist to want to fund water and sewer infrastructure in rural communities, but making an attempt to assess whether such a program is having the desired impact is important to do on a regular basis, if only to discuss loosening or tightening the application requirements.

Our ability to prescribe universal policy implications is tempered by the limitations of this research. First, in our choice of both outcome and control variables, we were limited by the availability of data at the community level. The explanatory power of these chosen variables is not remarkably high in our regression specifications. However, other potentially influential variables such as industry composition or job growth are typically not available at the community level. Second, several other federal programs (aside from USDA) assist rural communities with water infrastructure funding. These programs include the Environmental Protection Agency's Drinking Water State Revolving Fund, the Economic Development Administration's Public Works Grants, and the Department of Housing and Urban Development's Community Development Block Grants. Copeland (2010) specifies the percentage of these funds allocated to rural areas, typically approximately 20–30%. Including these other potential sources of infrastructure funding may alter the findings of this article. However, community-level data on where these funds were spent in Oklahoma for the time period in question were not readily available, and we consider this task as an extension to the work shown here. Similarly, the USDA's Single Family Housing program could have an influence on the results depicted in Table 5; discussion with the state RD director indicated that over 1000 single family housing loans were granted each year during the 1990s. Because most communities in the state benefitted from this program during this period, we believe that a dummy variable for housing program participation would lack enough variation to impact the results shown here. Still, the lack of data on this particular program is a limitation of the current study.

We have no way of knowing what type of growth the communities that did receive infrastructure funding would have had without it. In many cases, the USDA was the "lender of last resort" for these cities and without them, their water infrastructure situation would have continued to deteriorate. Furthermore, many of the communities that received funding were losing population and therefore could not meet the requirements for commercial loans (a declining tax base typically means less income for the town's budgets). Thus, the provision of water and sewer infrastructure in these areas is a "necessary but not sufficient" condition for economic growth, and this research has shown that in some cases, USDA funding for such infrastructure not only helps communities keep up, but also sometimes outgrow similar communities without funding.

One additional consideration is that households in areas where safe drinking water and wastewater standards are not met face the possibility of being relocated. Relocation costs in these instances are typically provided by the state or federal government. This was the case with the relocation of Cardin, Picher, and Hockerville in northern Ottawa County in Oklahoma as a result of pollution caused by abandoned lead and zinc mines (Stogsdill, 2012). In these cases, the provision of water/sewer infrastructure can be seen as a way of avoiding significant relocation costs. The average state and federal buyout offers for these Oklahoma communities were $54,000 and $65,000 per household, respectively (Stogsdill, 2012). This allows for a quick calculation regarding the federal and state funds saved by avoiding potential relocation and also allows for comparison with program costs (the average combined grant/loan amount in our dataset is $1.2 million). The water/sewer investments may not turn things around but can slow down the process of population decline and add viability to a community that had been regressing.

Generally, we have documented at least one long-term positive economic impact of the USDA RD water and sewer infrastructure program in Oklahoma. Documenting similar impacts for infrastructure programs in other states and across regions will be important as the fight for federal and state funds continues. Notably, statements about causality (as we have attempted to make here) can build strong cases for continued or increased funding.

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Appendix A. Full Results of All Eight Ordinary Least Squares Models (Long-Term: 1990–American Community Survey 2009)

	%Δ POP			%Δ MHI			%Δ PCI			%Δ HHE		
	Coefficient		SE	Coefficient		SE	Coefficient		SE	Coefficient		SE
% black 1990	–0.004	**	0.002	–0.002		0.001	–0.003	*	0.001	–0.004	***	0.001
% other race 1990	–0.003		0.002	–0.003		0.002	–0.005	***	0.002	0.000		0.001
% travel <15 minutes	–0.003	*	0.001	–0.001		0.001	0.000		0.001	0.000		0.001
% In labor force 1990	–0.002		0.004	0.001		0.003	0.002		0.003	0.002		0.002
% lacking complete plumbing 1990	0.003		0.007	0.001		0.007	–0.002		0.005	0.003		0.005
Median year structure built 1990	0.009	***	0.002	–0.002		0.002	–0.004	***	0.002	–0.001		0.001
Ln population density 1990	0.027		0.029	–0.003		0.014	–0.027	*	0.014	0.009		0.009
Unemployment rate 1990	–0.003		0.011	–0.003		0.008	0.005		0.007	–0.004		0.005
% with Bachelor's degree 1990	0.004		0.005	–0.008	***	0.003	–0.011	***	0.003	–0.003		0.002
Ln per-capita income 1990	0.184		0.160	–0.744	***	0.119	–0.862	***	0.094	–0.164	**	0.081
% households with earnings 1990	–0.003		0.004	0.003		0.003	0.001		0.002	–0.012	***	0.002
% households with self-employment income 1990	–0.005		0.004	0.002		0.002	0.004	**	0.001	0.000		0.001
% in poverty 1990	0.001		0.003	–0.001		0.002	0.000		0.002	–0.004	***	0.002
% vacant housing 1990	0.006	*	0.003	–0.003	*	0.002	0.001		0.002	–0.001		0.002
Ln population 1990	0.024		0.021	–0.017		0.013	–0.015		0.013	0.007		0.009
Ln median house value 1990	0.283	***	0.100	0.162	***	0.058	0.207	***	0.055	0.020		0.040
Rural–Urban Commuting Area codes 1990	0.017	**	0.008	0.000		0.005	–0.005		0.005	–0.007	*	0.004
Funding received	0.046		0.037	–0.013		0.028	–0.022		0.024	0.016		0.016
Constant	21.739	***	4.904	10.990	***	3.552	15.773	***	3.027	3.837		2.920
R^2	0.169			0.285			0.245			0.182		

	%Δ HHSEI			%Δ POV			%Δ VHU			%Δ MHV		
	Coefficient		SE	Coefficient		SE	Coefficient		SE	Coefficient		SE
% black 1990	–0.003		0.003	0.007	**	0.003	0.004	**	0.0020	0.001		0.001
% other race 1990	–0.005		0.003	0.005		0.004	0.004		0.0030	0.001		0.001
% travel <15 minutes	0.000		0.002	0.000		0.002	0.000		0.0020	–0.002	**	0.001
% In labor force 1990	–0.001		0.005	–0.010	*	0.006	–0.003		0.0040	–0.002		0.002
% lacking complete plumbing 1990	0.000		0.013	0.004		0.011	0.004		0.0090	0.005		0.006
Median year structure built 1990	0.000		0.003	0.011	***	0.004	–0.007	**	0.0030	0.004	**	0.002

Appendix A. Continued

	%Δ HHSEI			%Δ POV			%Δ VHU			%Δ MHV		
	Coefficient		SE	Coefficient		SE	Coefficient		SE	Coefficient		SE
Ln population density 1990	–0.093	***	0.029	0.007		0.034	0.009		0.0310	–0.029	**	0.014
Unemployment rate 1990	–0.045	***	0.016	–0.008		0.016	0.007		0.0140	0.005		0.008
% with Bachelor's degree 1990	–0.018	***	0.006	–0.002		0.008	–0.001		0.0050	–0.008	**	0.003
Ln per-capita inc 1990	–0.020		0.207	–0.034		0.204	0.157		0.1820	0.231	**	0.096
% households with earnings 1990	–0.001		0.005	–0.001		0.004	–0.006		0.0040	0.000		0.002
% households with self-employment income 1990	–0.041	***	0.005	–0.003		0.005	0.005		0.0040	–0.002		0.002
% in poverty 1990	–0.004		0.004	–0.037	***	0.005	0.000		0.0030	0.000		0.002
% vacant housing 1990	–0.004		0.003	0.003		0.004	–0.033	***	0.0040	0.001		0.002
Ln population 1990	–0.075	***	0.026	0.067	**	0.031	–0.034		0.0270	0.037	***	0.013
Ln median house value 1990	–0.113		0.131	–0.296	**	0.131	–0.276	**	0.1270	–0.460	***	0.065
Rural–Urban Commuting Area codes 1990	0.010		0.010	0.005		0.012	0.012		0.0100	–0.005		0.005
Funding received	0.022		0.058	0.031		0.060	0.031		0.0510	0.047	*	0.027
Constant	5.299		7.000	–17.255	**	8.302	16.393	**	6.5100	–4.664		4.190
R^2	0.253			0.245			0.297			0.190		

Note: *, **, and *** indicate statistical significance at the $p = 0.10$, 0.05, and 0.01 levels, respectively.
Standard errors (SEs) reported are robust standard errors through the Huber-White methodology.

Appendix B. Full Logistic Regression of Funding Received Variable

	Coefficient		SE
% black 1990	0.015	*	0.009
% other race 1990	–0.009		0.012
% travel <15 minutes	0.015	**	0.008
% in labor force 1990	0.035	*	0.018
% lacking complete plumbing 1990	–0.082	*	0.045
Median year structure built	0.025	*	0.014
Ln population density 1990	0.023		0.131
Unemployment rate 1990	0.109	*	0.063
% with less than Bachelor's degree 1990	–0.027		0.024
Ln per-capita income 1990	–1.250		0.771
% households with earnings 1990	–0.035	*	0.019
% households with self-employment income 1990	–0.016		0.016
% in poverty 1990	–0.019		0.016
% vacant housing 1990	–0.007		0.014
Ln population 1990	0.111		0.118
Ln median house value 1990	–1.168	**	0.492
Rural–Urban Commuting Area codes 1990	0.005		0.043
Constant	–23.544		27.407
Log likelihood		–288.104	
Pseudo R^2		0.092	

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