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Abstract

Does municipal broadband stimulate broadband adoption or employment growth? I conduct an empirical study of American towns that have built municipal networks to answer this question. Using data from the FCC's Form 477 and the U.S. Census Bureau's American Community Survey, I track broadband deployment, adoption, and employment statistics for these towns from 2013 to 2017. A town's decision to install a municipal network in the first place is not random, however. To deal with selection effects, I apply Coarsened Exact Matching to ordinary least squares regression to compare results from the treatment group with a weighted control group of similar towns. I also apply two-stage least squares regression with instrumental variable analysis to deal with endogeneity in the decision to build. I do not find evidence that municipal broadband yields benefits in broadband subscription rates or employment growth.

Keywords: Broadband deployment, broadband adoption, municipal broadband

JEL Classification: L96

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1. Introduction

Municipal broadband is public infrastructure that may stimulate broadband adoption and employment growth. In theory, municipal networks might enhance welfare by providing residents with an additional broadband provider, leading to lower prices and higher quality service. Empirical evidence has not proven whether this theory is true, however. This paper seeks to measure the economic effects of municipal broadband in order to test this claim.

Over 500 towns and cities have built their own broadband networks, generating data for investigation. Measuring effects of public investment requires some care to control for differences in town demographics and selection bias. Because the choice to build a network is not random, endogeneity is a concern for causal analysis. To control for selection bias, I use the Coarsened Exact Matching method with ordinary least squares regression and an instrumental variable in two-stage least squares regression to measure effects of municipal broadband.

Public provision of private goods often results in losses rather than gains for residents, such as the case of municipally-funded sports stadiums.[2] Public funds spent on Olympic stadiums have generated long-term debt obligations for local residents internationally as well.[3] Municipal broadband follows a similar pattern of high fixed-cost investment and long-term debt in towns and cities. Many small towns have built their own networks, only to sell them at a loss to private operators a few years later. Electric utilities often incur net operating losses in broadband provision as well.[4] Debt payments are structured on expectations of future revenue,[5] but forecasts are often wrong, leading to long-term liabilities for local residents.

2. What Are the Economic Effects of Municipal Broadband?

To investigate whether municipal broadband yields economic benefits across towns and cities, I apply empirical methods to existing datasets. My null hypothesis is that municipal broadband has no effect on broadband adoption or employment growth. I seek to falsify this claim. If I find statistically significant results, then I can say that municipal broadband affects these outcome measures. If I do not find statistically significant results, then I cannot prove the claim.

Broadband adoption studies use propensity score matching and average treatment effects to estimate causal effects (Whitacre, Gallardo, Strover, 2014). Matching is a standard method in causal analysis of heterogeneous samples (Imbens and Woolridge, 2009).

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[2] Zaretsky (2001); Coates and Humphreys (1999); Noll (1997).
[3] Flyvbjerg (2016).
[4] Columbia Power & Water Systems has over 6,500 broadband subscribers, $7.7 million in broadband revenues, and $6.7 million in broadband operating expenses, generating a net loss of $155,814 in total non-operating expenses after interest expenses of $141,446 on debt service on $7.6 million in revenue and tax bonds, which amounts to $1,308.69 per customer. CP&WS, *Enterprise Funds of the City of Columbia, Tennessee, Comprehensive Annual Financial Report, For Fiscal Years Ended June 30, 2017 and June 30, 2016*, https://cpws.com/wp-content/uploads/2017/12/FY_2017_CAFR.pdf.
[5] Yoo and Pfenninger (2018).

The Coarsened Exact Matching (CEM) method has been used to compare towns and cities in studies of broadband (Ford, 2018, 2019). Towns are very different from each other in population, income, age, density, employment, education, and ethnicity. Because municipalities vary in demographic characteristics, comparison of outcomes requires care. Without matching methods to generate weighted control groups, comparisons across towns are statistically deficient, as cataloged by Ford (2018).

I apply the CEM method to generate a weighted control group of places that have similar characteristics as places with municipal broadband. I use this method combined with ordinary least squares regression to measure effects of municipal broadband.

Broadband deployment is not a random process. The decision to build a municipal broadband network is endogenous to its success. A town that builds a network may have better finances, a population that buys more broadband, and population inflows from existing job growth. A town that builds a network may also depend on state and federal subsidies to build its own infrastructure in remote areas. Many local factors determine the success of a municipal network, aside from the project itself. I seek to separate out local conditions from the public investment itself.

This causation question has been studied in other papers. Broadband subscriptions increase with the number of broadband providers, which may seem to indicate that supply drives demand. On close inspection, however, uptake is better explained by demand rather than supply (Wallsten and Mallahan, 2013). Providers build broadband in areas with growing demand, which results in higher subscription rates. Demand drives supply, rather than supply driving demand.

A study of the effects of municipal broadband on subscriptions and employment growth requires causal analysis that takes into account this endogeneity problem. To test for causality, I select an instrumental variable that may influence a decision to build broadband but not influence the decision to subscribe, except through its effects on the initial decision.

3. OLS with CEM Matching

I start with a dataset of American towns and cities with municipal broadband from lists published by the Institute of Local Self-Reliance (ILSR) and *Broadband Communities Magazine*. The ILSR maintains a crowd-sourced database of localities that operate their own broadband networks. In one dataset, the ILSR includes 528 municipalities with publicly-funded broadband.[6] The *Broadband Communities Magazine* cites 210 municipal providers with fiber-to-the-home broadband service in a Fiberville dataset.[7]

[6] BroadbandNow, Institute of Local Self-Reliance, "Community Broadband Networks Across the United States," https://broadbandnow.com/report/community-broadband-networks-across-us/ (listing more than 520 municipal providers of partial, fiber, cable, dark, and INET service).

[7] Fiberville, *Broadband Communities Magazine*, http://www.bbpmag.com/search.php (listing more than 1150 providers, 210 of which are municipal providers with fiber-to-the-home).

From these lists, I searched for municipal providers that filed Form 477 data with the Federal Communications Commission (FCC). Form 477 data is self-reported by service providers at the census block level. Providers record details of their service offerings, including whether they offer business or commercial service, their maximum advertised and actual speeds, holding company names, doing-business-as names, and types of technology used to deliver broadband. I conducted queries on Form 477 data on provider names, town names, and other identifying information on each of the 528 municipalities in the ILSR list and the 210 providers in the Fiberville dataset. Of the 528, I found only 71 municipal providers who filed data in 2014, 2015, and 2016. These providers are listed in the Appendix.

Broadband adoption data is available in the U.S. Census Bureau's American Community Survey (ACS). The ACS measures household broadband subscription rates in approximately 623 places and towns from 2013 to 2017. Survey questions are sent to households selected and weighted to represent all American households.

Of 71 municipal providers with Form 477 data, 14 are located in 22 places with ACS data.[8] Since the Census Bureau randomizes its selection of places for the ACS survey, I consider these 22 places to be sufficiently randomized for an empirical study.

With provider data, subscription rates, and employment data, I have observations for a total of 385 places, 22 of which have municipal broadband and 363 of which do not. Descriptive statistics show a treatment group of 22 places with municipal broadband and a total control group of 363 places.

Using the CEM method, I generated a weighted control group of 24 places to resemble the treatment group. The CEM method matches on covariate dimensions to generate a weighted control group.[9] Exact matching of a control and treatment group would require that all places be identical along covariates, which is not possible for studies of towns and cities. I selected town demographics of population, population density, median age, and median income to generate the weighted control group.

Table 1 shows the number of places in the treatment group, full control group, and weighted control group. Table 2 presents a comparison of description statistics of these groups. The weighted control group appears to have on average, lower broadband subscriber rates than the treatment group and the unweighted control group. The weighted control group also appears to include fewer providers than the treatment group and control group.[10]

[8] I matched Form 477 deployment data by census block with ACS adoption data by census place using the MABLE/Geocorr14: Geographic Correspondence Engine.

[9] The CEM method is a new matching method used to reduce imbalance between treated and control groups. (Iacus, King, and Porro, 2008). The CEM method has benefits over existing matching methods. The method is easier to understand, requires fewer assumptions, and possesses better statistical properties than other methods. (Blackwell, et al., 2010).

[10] The CEM method first coarsens the data, applies an exact match on coarsened data, then runs analysis on uncoarsened, matched data (Blackwell, et al., 2010). The CEM method is in a class of matching methods called Monotonic Imbalance Bounding (MIB) (*Id*.). Matching methods are used to ensure that the control and treatment groups are balanced, meaning that the distribution of covariates are more similar (*Id*. at 2). Several approximate

Table 1. CEM Matching.

Census Places	Not Matched	CEM Matched	Total
No Municipal Broadband	339	24	363
Municipal Broadband	12	10	22
Total	351	34	385

Table 2. Descriptive Statistics.

Variable	Treatment Group	Control Group	CEM Weighted Control Group
Total Census Places	22	363	24
Total Census Blocks	4,215	3,274	2,865
Total Census Blocks with Municipal Broadband	452	0	0
Total Number of States	11	41	25
	Average Per Census Place		
Broadband Subscriber Rate (ACS 2013)	73.78	74.04	71.58
Broadband Subscriber Rate (ACS 2014)	74.84	75.65	73.18
Broadband Subscriber Rate (ACS 2015)	76.65	77.21	75.09
Broadband Subscriber Rate (ACS 2016)	81.45	81.70	79.48
Broadband Subscriber Rate (ACS 2017)	83.13	83.62	81.88
Number of Providers 10 Mbps (FCC 2014)	3.44	3.65	3.31
Number of Providers 25 Mbps (FCC 2014)	1.57	1.35	1.14
Number of Non-Municipal Providers 10 Mbps	2.44	3.37	3.31
Number of Non-Municipal Providers 25 Mbps	0.57	1.35	1.14
Population (2016)	172,747	173,840	110,123
Population Density (Pop/Sq. Mi.)	3,308	4,006	2,712
Land Area (Sq. Mi.)	72	1882	53
Median Age (2016)	34.2	35.7	33.9
Median Income (2016)	$76,269	$78,929	$68,499
Labor Force Participation Rate (2016)	64.61	65.39	65.48
Unemployment Rate (2016)	5.2	5.8	5.7

Table 3. Univariate Imbalance.

Covariates	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Population	.025	.0316	.02119	.13828	-.03391	-.07307	.29587
Population Density	.40833	-.00052	-.00998	-.2907	.25061	.14434	-.21517
Median Age	.1	.00516	-.07223	.00623	-.00292	.04445	.01084
Median Income	.1	.0005	-.01897	.02373	.00137	-.03636	.15618

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matching methods are used to find comparable control groups and treatment groups based on a propensity score (or Mahalanobis distance) (*Id*. at 2). Preprocessing and postprocessing techniques can be applied to mitigate limitations of propensity score matching (*Id*.) The CEM method finds common empirical support between the control and treatment groups (*Id*. at 4). The CEM method meets the congruence principle which allows the algorithm to match data better (*Id*.).

The $\mathcal{L}_1$statistic compares the control and treatment groups for balance among place-level covariates.[11] The multivariate $\mathcal{L}_1$ distance of the CEM weighted control group is 0.5083. Perfect global balance would have an $\mathcal{L}_1$ distance of 0, and a larger distance means greater imbalance between groups to a maximum $\mathcal{L}_1$ distance of 1. The $\mathcal{L}_1$ distance is valuable to compare matching solutions, but has limited relevance on its own.[12] Table 3 shows the univariate imbalance in the CEM weighted control group.

a. Empirical Strategy

Does municipal broadband yield increases in subscription rates or employment growth? Using ordinary least squares, I estimate the effects on the change in subscription rates across the treatment group and weighted control group. Equation (1) shows the regression model.

$$ln\left(Y_{i,t}/Y_{i,t-4}\right) = \delta T_i + \beta^j ln\left(B^j_{i,t-3}\right) + \gamma X_i + \lambda_k + \varepsilon_i \qquad (1)$$

The dependent variable is shown as the natural log of the change in Y_i, for each place *i*, from year *t* and *t-4*, where *t* = 2017 and *t-4* = 2013. I generate 3 sets of results where Y_i is replaced with household subscription rates S_i, unemployment rate U_i, and labor force participation rate L_i.

The independent variable $T_i = 1$ is the treatment group with municipal broadband and $T_i = 0$ for the weighted control group without municipal broadband for each place *i*. The treatment effect is measured by δ which estimates the effect of the treatment on economic outcomes caused by the presence of municipal broadband.

The independent variable $B^j_{i,t}$ is the average number of non-municipal broadband providers of *j* Mbps in a census block in place *i* in year *t-3* = 2014. The coefficient β estimates the effect of competition in each place. In places with a municipal network, I subtract one from the average number of providers reported in census blocks in each place to get the number of non-municipal providers. The number of non-municipal providers provides information on how much competition a municipal network generates. If a municipal network is 1 among 2 providers or 1 among 3 providers, the presence of the municipal network will have a larger or smaller effect on outcomes.

Municipal networks offer different tiers of service as self-reported in Form 477. I do not account for the particular speed of the municipal network in each place due to limited observations. I assume that each municipal network offers 10 Mbps and 25 Mbps. The ILSR and Fiberville datasets report on technology offered by municipal networks, most of which offer high-speed broadband through fiber or cable lines.

Covariates are included in vector X_i. Place-specific demographics include median age, median income, population, and population density, each of which are natural log transformed. The coefficient γ represents the effect of each demographic on the dependent variable. I include

[11] The CEM method provides a $\mathcal{L}_1$ statistic to measure imbalance between the control and treatment groups (*Id*. at 5). The statistic includes imbalance for a full joint distribution including all interactions of the covariates (*Id*. at 6).
[12] Blackwell, et al., 2010, at 6.

λ_k for state-level fixed effects and ε_i is the error term. Robust standard errors account for heterogeneity in the error term.

b. Results

Table 4 presents the treatment effect of municipal broadband on change in household broadband subscription rates S_i. In the treatment group of places with municipal broadband, $T_i = 1$, no effect can be found in the coefficient, δ, compared to the weighted control group of $T_i = 0$. Columns (1) to (5) show that results lack statistical significance at the 1, 5, or 10% level.

Column (1) shows the results of a regression without CEM Matching. The constant has statistical significance with 379 observations but the effect, δ, on the treatment group $T_i = 1$ has no statistical significance.

Column (2) shows results without CEM Matching and with covariates of population, population density, median age, and medium income. The constant has statistical significance with 359 observations. Median income appears to have an effect on the change in subscription rate. For increases in median income, change in subscription rates decreases. The interpretation of this result are less relevant than the lack of statistical significance on the treatment effect of interest.

Column (3) shows results from CEM matching with 32 observations. The treatment effect is not statistically significant. I do not find empirical effect of municipal broadband on changes in subscription rates.

Columns (4) and (5) include additional covariates and state fixed effects with CEM matching. The results have higher R^2 values perhaps from over-fitting and the constant term is not statistically significant, which does not satisfy the least squares criterion. The treatment effect is not statistically significant.

Table 5 and Table 6 show treatment effects of municipal broadband on changes in unemployment rates and changes in labor force participation rates. Like Table 4, these results lack statistical significance for the coefficient of interest, δ, on the treatment group of places with municipal broadband.

Table 5 shows statistically significant effects of municipal broadband in Columns (1) and (2) without CEM matching. The negative coefficient indicates that the change in unemployment rate decreased in towns with municipal broadband. This would appear to be a promising result, except for a few qualifying considerations. The R^2 of the result in Column (1) is small at 0.015 even though the constant term is statistically significant. The constant term in Column (2) is not statistically significant, which does not satisfy the least squares criterion. With CEM matching results in Columns (3), (4), and (5), there is no statistical effect of the treatment on the change in unemployment rate.

Some of the covariates show statistically significant effects but are generally irrelevant for this investigation. Median age appears to have some effect on changes in unemployment rate. The coefficient on that covariate is negative and statistically significant in Column (2) in Table 5.

The younger the population of a place, a positive change in unemployment rate is measured. Median income appears to have some effect on change in labor force participation rate. The coefficient on that covariate is negative and statistically significant in Column (4) in Table 6.

For each of the regressions, I run F-tests for joint significance to confirm that multivariate regression is appropriate with these covariates. I test whether the number of non-municipal providers and covariates are jointly zero. For some regressions, the models do not pass the joint significance test. This may be due to the speed tier data. The number of non-municipal providers of 10 Mbps is a subset of the number of non-municipal providers of 25 Mbps, which may lead to joint significance.

Table 4. Effect on Broadband Subscriptions.

OLS with CEM Matching	**Change in Household Broadband Subscription Rate**				
	(1)	(2)	(3)	(4)	(5)
Municipal Broadband	-0.02	-0.01	-0.02	0.02	-0.07
	(0.02)	(0.02)	(0.04)	(0.03)	(0.09)
Number of Other 10 Mbps Providers	0.00	0.01	-0.05	-0.04	0.05
	(0.02)	(0.02)	(0.07)	(0.05)	(0.22)
Number of Other 25 Mbps Providers	-0.02*	-0.02*	-0.04	-0.02	-0.09
	(0.01)	(0.01)	(0.04)	(0.03)	(0.11)
Population		0.01		-0.00	
		(0.01)		(0.02)	
Population Density		0.01		0.03	
		(0.01)		(0.04)	
Median Age		-0.03		-0.42**	
		(0.04)		(0.15)	
Median Income		-0.11***		-0.14***	
		(0.01)		(0.05)	
CEM Matching	No	No	Yes	Yes	Yes
State Fixed Effects	No	No	No	No	Yes
Constant	0.13***	1.33***	0.19**	3.00***	0.15
	(0.03)	(0.24)	(0.08)	(0.46)	(0.26)
Observations	379	359	32	32	32
R-squared	0.011	0.148	0.087	0.408	0.814
F-Test of Joint Significance	F(3,375) =1.24	F(7,351) =10.54	F(3,28) =1.25	F(7,24) =15.95	F(3,12) =1.99
Prob > F	0.29	0.00	0.31	0.00	0.17

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Effect on Unemployment Rate.

OLS with CEM Matching	**Change in Unemployment Rate**				
	(1)	(2)	(3)	(4)	(5)
Municipal Broadband	-0.07*	-0.08**	-0.09	-0.08	-0.12
	(0.04)	(0.04)	(0.07)	(0.09)	(0.23)
Number of Other 10 Mbps Providers	-0.01	-0.02	0.04	0.01	-0.15
	(0.04)	(0.04)	(0.13)	(0.14)	(0.63)
Number of Other 25 Mbps Providers	-0.04*	-0.03	-0.10*	-0.09	0.02
	(0.02)	(0.02)	(0.06)	(0.07)	(0.31)
Population		-0.00		-0.02	
		(0.01)		(0.05)	
Population Density		0.00		-0.10	
		(0.01)		(0.11)	
Median Age		-0.35***		-0.52	
		(0.08)		(0.54)	
Median Income		0.03		0.21	
		(0.03)		(0.16)	
CEM Matching	No	No	Yes	Yes	Yes
State Fixed Effects	No	No	No	No	Yes
Constant	-0.37***	0.58	-0.37**	0.14	-0.25
	(0.05)	(0.42)	(0.15)	(1.69)	(0.75)
Observations	380	360	32	32	32
R-squared	0.015	0.064	0.087	0.158	0.728
F-Test of Joint Significance	F(3,376) =2.50	F(7,352) =3.04	F(3,28) =1.53	F(7,24) =0.91	F(3,12) =0.48
Prob > F	0.06	0.00	0.23	0.52	0.70

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Effect on Labor Force Participation Rate.

OLS with CEM Matching	**Change in Labor Force Participation Rate**				
	(1)	(2)	(3)	(4)	(5)
Municipal Broadband	0.00	-0.00	0.00	0.01	0.02
	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
Number of Other 10 Mbps Providers	0.00	-0.00	-0.02	-0.01	-0.02
	(0.00)	(0.00)	(0.02)	(0.02)	(0.05)
Number of Other 25 Mbps Providers	-0.00*	-0.00	-0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
Population		0.00		0.00	
		(0.00)		(0.00)	
Population Density		0.00		0.01	
		(0.00)		(0.01)	
Median Age		-0.06***		-0.00	
		(0.01)		(0.05)	
Median Income		-0.00		-0.03**	
		(0.00)		(0.02)	
CEM Matching	No	No	Yes	Yes	Yes
State Fixed Effects	No	No	No	No	Yes
Constant	-0.01**	0.20***	0.01	0.22	-0.01
	(0.01)	(0.06)	(0.02)	(0.13)	(0.06)
Observations	380	360	32	32	32
R-squared	0.008	0.112	0.133	0.300	0.670
F-Test of Joint Significance	F(3,376) =1.49	F(7,352) =6.50	F(3,28) =2.42	F(7,24) =5.71	F(3,12) =3.17
Prob > F	0.22	0.00	0.09	0.00	0.06

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4. Two-Stage Least Squares Regression

Since the deployment of municipal broadband is not random, I proceed to identify an instrumental variable to assist with causal analysis. For two-stage least squares regression, I select an instrumental variable of partisanship of voters in each town or city. I use data from Cook's Partisan Voting Index (CPVI), published annually in *The Almanac of American Politics*, to measure the partisanship of voters in each census place in my dataset.

Left-leaning and right-leaning voters may have different preferences for public infrastructure. Towns with left-leaning voters may be more inclined to build municipal broadband, while right-leaning voters may disfavor public provision of private goods.

While the partisanship of voters in a town may explain the decision to build a municipal network, partisanship should not affect the uptake rate of broadband subscriptions. Demand for broadband is probably not influenced by the partisanship of a household. If partisanship of voters does not affect subscription rates, but explains the decision to build municipal broadband, then an instrumental variable of partisanship may control for endogeneity.

The CPVI offers an overall assessment of partisan strength in Congressional districts in presidential elections. The CPVI is an index that compares the district average of the party nominee compared to the national value of the party nominee (Barone & Cohen, 2006, at 14). For example, a CPVI value of R+15 represents a district that voted 15 percentage points higher for the Republican candidate than the national voting share for the Republican candidate. A CPVI value of D+15 in a district means that district voted 15 percentage points higher for the Democratic candidate than the national voting share for the Democratic candidate. A district with a +0 is an evenly balanced district.

In my dataset, I denote right-leaning districts with positive indices and left-leaning districts with negative indices. I try several different formulations of CPVI to find a suitable instrumental variable. I ultimately select the CPVI from the 2006 almanac, *ln(CPVI2006)*, representing the average CPVI of the 2000 and 2004 presidential elections, since it has the strongest statistical results. I tested other variations such as the average CPVI from the last 6 presidential elections in years 2000, 2004, 2008, 2012, and 2016, denoted as *ln(ACVPI)*.[13] I generate other formulations of CPVI, such as *ln(ACPVI0617)*, the average of CPVI for the almanac editions of 2006 and 2017. I also test *ln(CPVI2017)* from the 2017 almanac, representing the average CPVI of the 2012 and 2016 presidential elections.

Further studies may consider other ideas for instrumental variables. For instance, proximity of a town to a university system may serve as an alternative. If a town with a student

[13] The CPVI published in 2006 is an average of the 2000 and 2004 presidential elections (Barone & Cohen, 2006). The CPVI published in 2010 is an average of the 2004 and 2008 presidential elections (Barone & Cohen, 2010). The CPVI published in 2014 is an average of the 2008 and 2012 presidential elections (Barone & Cohen, 2014). The CPVI published in 2017 is an average of the 2012 and 2016 presidential elections (Barone & Cohen, 2017). I generate an ACPVI which is the average of the index from 2000 and 2004, 2004 and 2008, 2008 and 2012, and 2012 and 2016.

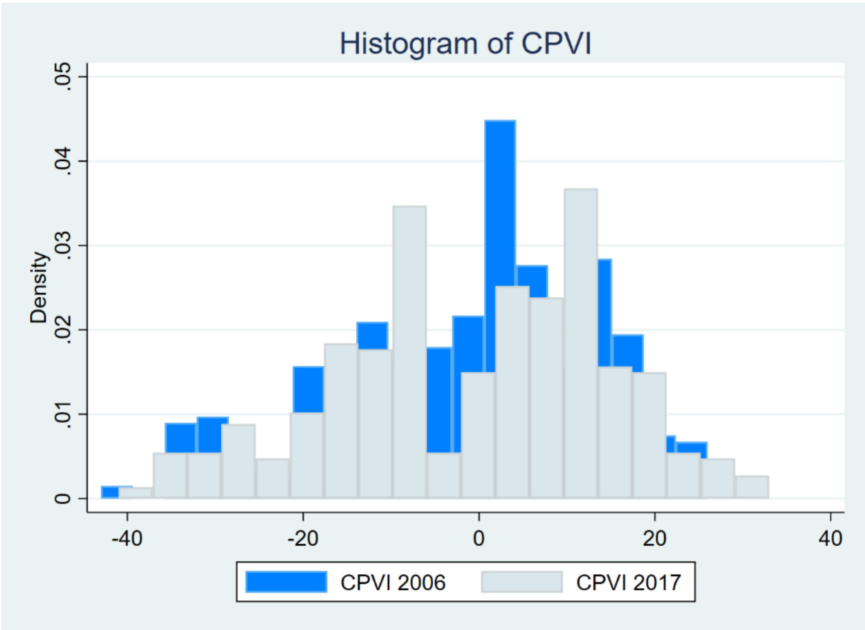
population has a steady flow of income from university activity, the town council may be more inclined to build publicly-funded infrastructure.

Table 7 presents descriptive statistics for the CPVI data in each place in my dataset. Places in my dataset have a mean CPVI near 0, with a slight left-leaning trend. Partisanship of voters changes over time, but the general partisan leaning per place is fairly stable. The range between the most left-leaning and most right-leaning places range from 33 percentage points above 0 and 41 percentage points below 0 as seen in the CPVI from the 2017 almanac. The histogram in Figure 1 shows changes in partisanship per place between the 2006 almanac and 2017 almanac.

Table 7. Descriptive Statistics for Cook's Partisan Voting Index (CPVI) Per Place.

Variable	Obs.	Mean	S.D.	Min	Max
CPVI 2006	368	-0.92	14.52	-43	26
CPVI 2010	368	-0.53	14.69	-41	29
CPVI 2014	375	-0.31	15.33	-42	32
CPVI 2017	377	-0.60	15.56	-41	33
Avg(CPVI 2006-CPVI 2017)	377	-0.64	14.21	-36	29.8
SD(CPVI 2006-CPVI 2017)	377	3.55	3.34	0	23.0
CPVI 2017 / CPVI 2006	362	0.77	2.98	-20.5	13
Avg(CPVI 2006, CPVI 2017)	377	-0.84	14.32	-36.5	29

Figure 1. Histogram of CPVI Per Place.



a. Empirical Strategy

Equations (2) and (3) show the first and second-stage equations for the two-stage least squares model. M_i represents the decision to build municipal broadband as instrumented by *ln(CPVI2006)*, representing the average CPVI of the 2000 and 2004 presidential elections from the 2006 almanac.

$$M_i = \beta_0 + \beta_1^j ln\left(B_{i,t-3}^j\right) + \gamma X_i + v_i \tag{2}$$

$$ln\left(Y_{i,t}/Y_{i,t-4}\right) = \delta_0 + \delta_1 M_i + \delta_1^j ln\left(B_{i,t-3}^j\right) + \gamma X_i + u_i \tag{3}$$

The dependent variable is the natural log of the change in Y_i, the output variable of interest for each place *i,* between 2013 and 2017. I generate 3 sets of results to test effects of municipal broadband for changes in household broadband subscriptions S_i, unemployment rate U_i, and labor force participation rate L_i.

I include covariates, $B_{i,t-3}^j$, to control for the number of non-municipal providers in speed tiers *j* = 10 Mbps and 25 Mbps in each place *i*. The number of non-municipal providers represents a measure of competition in the local market. Additional covariates represented by vector X_i include the natural log transformation of median age, median income, population, and population density in each place *i*. I assume that municipal networks that submitted Form 477 data to the FCC in *t-3* = 2014 did not exit the market before *t* = 2017.[14]

b. Results

Table 8 presents a summary of first and second-stage results from regressions on change in household broadband subscription rates, change in unemployment rates, and change in labor force participation rates. The second-stage results in Table 8 reflect Column (2) of Tables 9, 10, and 11.

First-stage results show that the instrumental variable of *ln(CPVI2006)* appears to be a strong instrumental variable for the non-random decision to build municipal broadband. I tested other variations of the CPVI including the average over the years, the average of the first and last year available, the voting index for the latest series in 2017. I found that the CPVI for the earliest available almanac in 2006 had the strongest performance as an instrument. The instrument has statistical significance at the 10% level.

[14] The Appendix shows the start dates for the 71 municipal networks with Form 477 data. Several of these networks are listed in the Fiberville database as having been established as late as 2015 and 2016, but submitted deployment data to the FCC as early as 2014. I rely on the FCC data. The 14 municipal networks in the 22 places matched by the CEM algorithm include Algona Municipal Utilities, Braintree Electric Light Department, BVU OptiNet, Cedar Falls Utilities, City of Columbus, City of Ellensberg, Tacoma Power Click! Network, Eastern Shore of Virginia Broadband Authority, EPB Fiber Optics, Jackson Energy Authority, Gainesville Regional Utilities, Holyoke Gas & Electric Department, Lake County Lake Connections, and Spanish Fork Community Network.

Second-stage results show that the presence of a municipal broadband provider has no statistically significant effect on change in broadband subscription rate, unemployment rate, or labor force participation rate. Each of the coefficients, δ_1, are not statistically significant.

Tables 9, 10, and 11 present detailed results from two-stage least squares regressions on the 3 outcomes of interest. The treatment effect is not statistically significant. From these results, I cannot prove an economic effect of municipal broadband on changes in adoption and employment.

Table 8. Summary of First and Second-Stage Results.

	First-Stage Results	**Second-Stage Results**		
	Municipal Broadband			
		Change in Household Broadband Subscription Rate	Change in Unemployment Rate	Change in Labor Force Participation Rate
ln(CPVI2006)	0.02*			
	(1.67)			
Number of Other 10 Mbps Providers	-0.03	0.01	-0.06	0.01
	(-0.51)	(0.32)	(-1.00)	(1.07)
Number of Other 25 Mbps Providers	-0.08**	-0.01	-0.03	-0.01
	(-2.40)	(-0.25)	(-0.53)	(-0.94)
Municipal Broadband		-0.07	0.18	0.01
		(-0.21)	(0.29)	(0.09)

Absolute value of t-statistic in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 9. Effect on Broadband Subscription Rate.

2SLS	Change in Household Broadband Subscription Rate		
	(1)	(2)	(3)
Municipal Broadband	-0.05	-0.07	0.09
	(-0.20)	(-0.21)	(0.25)
Number of Other 10 Mbps Providers		0.01	0.01
		(0.32)	(0.37)
Number of Other 25 Mbps Providers		-0.01	0.01
		(-0.25)	(0.25)
Population			-0.01
			(-0.48)
Population Density			0.03*
			(2.05)
Median Age			-0.01
			(-0.11)
Median Income			-0.10***
			(-3.55)
Constant	0.12***	0.12**	1.15**
	(9.93)	(2.75)	(3.19)
Observations	201	200	183
First-Stage R^2	0.02	0.06	0.08
First-Stage Adjusted R^2	0.01	0.04	0.04
First-Stage Partial R^2	0.02	0.01	0.01
First-Stage F	F(1,199)= 3.38	F(1,196)=2.79	F(1,175)=2.08
First-Stage Prob > F	0.07	0.10	0.15

Absolute value of t-statistic in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 10. Effect on Unemployment Rate.

2SLS	**Change in Unemployment Rate**		
	(1)	(2)	(3)
Municipal Broadband	0.13	0.18	-0.85
	(0.24)	(0.29)	(-1.03)
Number of Other 10 Mbps Providers		-0.06	-0.11
		(-1.00)	(-1.44)
Number of Other 25 Mbps Providers		-0.03	-0.10
		(-0.53)	(-1.21)
Population			0.03
			(0.77)
Population Density			-0.00
			(-0.15)
Median Age			-0.50**
			(-2.89)
Median Income			0.00
			(0.06)
Constant	-0.40***	-0.33***	1.22
	(-16.17)	(-3.95)	(1.42)
Observations	201	200	183
First-Stage R^2	0.02	0.06	0.08
First-Stage Adjusted R^2	0.01	0.04	0.04
First-Stage Partial R^2	0.02	0.01	0.01
First-Stage F	F(1,199)=3.38	F(1,196)=2.79	F(1,175)=2.08
First-Stage Prob > F	0.07	0.10	0.15

Absolute value of t-statistic in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 11. Effect on Labor Force Participation Rate.

2SLS	Change in Labor Force Participation Rate		
	(1)	(2)	(3)
Municipal Broadband	0.02	0.01	-0.12
	(0.32)	(0.09)	(-1.03)
Number of Other 10 Mbps Providers		0.01	-0.00
		(1.07)	(-0.21)
Number of Other 25 Mbps Providers		-0.01	-0.01
		(-0.94)	(-1.22)
Population			0.00
			(0.56)
Population Density			-0.00
			(-0.38)
Median Age			-0.08**
			(-3.26)
Median Income			-0.01
			(-0.95)
Constant	-0.01***	-0.02	0.36**
	(-3.54)	(-1.86)	(2.97)
Observations	201	200	183
First-Stage R^2	0.02	0.06	0.08
First-Stage Adjusted R^2	0.01	0.04	0.04
First-Stage Partial R^2	0.02	0.01	0.01
First-Stage F	F(1.199)=3.38	F(1.196)=2.79	F(1,175)=2.08
First-Stage Prob > F	0.07	0.10	0.15

Absolute value of t-statistic in parentheses. * p<0.05, ** p<0.01, *** p<0.001

5. Discussion

I do not find economic benefits from municipal broadband in this empirical investigation. Based on data across towns and cities, I am unable to prove that municipal broadband yields any effect on changes in household broadband subscriptions, unemployment rates, or labor force participation rates.

The statistical non-significance of my results does not detract from the importance of the empirical investigation. (Abadie, 2018). Non-results, as defined by significance testing, are still important for empirical economics, even if researchers have traditionally followed a practice of only publishing results with point null rejections rather than non-rejections.

Limited data on broadband subscription rates, deployment rates, and employment rates suggests that economists should report findings of non-rejections with greater frequency. Statistical non-significance in the results of my investigation reveals deficiencies in claims that municipal broadband stimulates broadband adoption and employment growth.

6. Conclusion

I do not find evidence of economic benefits from municipal broadband across towns and cities. Using OLS and 2SLS, I am unable to find proof that municipal broadband yields gains in household broadband subscription rates or employment growth.

Empirical studies are important for city planners and policymakers who make decisions about public investment. Case studies and qualitative reports can offer insights into the performance of public projects, but empirical methods incorporate variation in heterogeneous samples.

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Appendix

Table 12. Data Sources

Variable	Series Name	Source
Municipal Broadband Providers	Provider List	Institute for Local Self-Reliance, Broadband Communities Magazine
Municipal Broadband Providers by Census Block	FCC Form 477	Form 477 2014, 2015, 2016
Municipal Broadband Providers by Census Place	FCC Form 477	Form 477 2014, 2015, 2016; MABLE/Geocorr14[15]
Number of Broadband Providers	FCC Form 477	Form 477 2014, 2015, 2016[16]
Technology Code	FCC Form 477	Form 477 2014, 2015, 2016[17]
Percent of Households with Broadband Internet Subscription	GCT2801: Percent of Households with a Broadband Internet Subscription by Census Place - Households	ACS_17_1YR_GCT2801, ACS_13_1YR_GCT2801,[18] HC01_EST_VC01; ACS_17_5YR_S2801,[19] HC01_EST_VC01
Unemployment Rate	S2301: Employment Status	ACS_17_5YR_S2301, ACS_13_5YR_S2301, HC04_EST_VC01
Labor Force Participation Rate	S2301: Employment Status	ACS_17_5YR_S2301, ACS_13_5YR_S2301, HC02_EST_VC01
Population	S2301: Employment Status	ACS_17_1YR_S2301, HC01_EST_VC01
Population Density	FCC Form 477, Population per Land Area in Square Miles by Census Blocks in each Census Place	FCC Form 477 2014, 2015, 2016[20]
Median Age	S0101: Age and Sex	ACS_17_1YR_S0101, HC01_EST_VC37: Median Age
Median Income	S1902: Mean Income in the Past 12 Months (in 2017 Inflation-Adjusted Dollars)	ACS_17_1YR_S1902, HC03_EST_VC02: Median Income

[15] Census places (2014) and census blocks (2010+) were matched using the Missouri Census Data Center, MABLE/Geocorr14: Geographic Correspondence Engine, http://mcdc.missouri.edu/websas/geocorr14.html. Land area in square miles was selected as the weighting variable for determining the portion of source geocodes corresponding to target geocodes.

[16] FCC Form 477: Fixed Broadband Deployment Data as of December 31, 2014 – Version 2 (Fixed with Satellite - Dec 14v2); Fixed Broadband Deployment Data as of June 30, 2015 - Version 3 (Fixed with Satellite - Jun 15v3); Fixed Broadband Deployment Data: December, 2016 Status V1 (Fixed without Satellite - Dec 16).

[17] Transmission technologies include Asymmetric xDSL, ADSL2, ADSL2+, VDSL, Symmetric xDSL, Other Copper Wireline, Cable Modem (other than DOCSIS 1, 1.1, 2.0, 3.0, or 3.1), Cable Modem (DOCSIS 1, 1.1 or 2.0), Cable Modem (DOCSIS 3.0), Cable Modem (DOCSIS 3.1), Optical Carrier / Fiber to the end user (Fiber to the home or business end user, does not include "fiber to the curb"), Satellite, Terrestrial Fixed Wireless, Electric Power Line, All Other. With census-block data from three years of Form 477 filings (2015-2017), I collapse the number of providers into speed tiers for places in the treatment and control groups. For each block and each year, I tally the number of providers with more than 1 Mbps of consumer maximum advertised download speeds, more than 10 Mbps, more than 25 Mbps, more than 50 Mbps, more than 100 Mbps, and more than 500 Mbps.

[18] ACS 1-Year Estimates (ACS_17_1YR_GCT2801, Sept. 13, 2018 (in selected states) County Subdivision Universe.

[19] *See generally* S2801: Types of Computers and Internet Subscriptions.

[20] FCC Staff Block Estimates: 2016 ("Data file provides housing unit, household and population counts for each block for 2010 (U.S. Census) and 2015 (Commission staff estimate)").

Table 13. Providers of Municipal Broadband with Form 477 Data.

FCC Form 477 FRN	Provider[21]	State	Form 477 Tech Code	ILSR Tech Listed	No. of Census Blocks	Deployment Type	Year Built	Potential Subscribers
5671128	Algona Municipal Utilities	IA	Fiber	Cable	390	Replace	2013	--
5920509	Auburn Essential Services	IN	Fiber	Fiber	706	Overbuild	2006	20,000
18595660	Bellevue Municipal Utilities	IA	Fiber	Fiber	213	Overbuild, Replace	2006	1,200
4122651	Benton County Public Utility District	WA	Fixed Wireless	Fiber	3517	Overbuild	2002	Businesses Only
18932350	Blink (Barbourville Utilities)	KY	Cable	Cable	317	Replace	2010	--
20910857	Bowling Green Municipal Utility	KY	Fiber	Partial	213	Overbuild	2007	Businesses Only
15437841	Braintree Electric Light Department	MA	Cable	Cable	488	Overbuild	2008	Businesses Only
6823991	BVU OptiNet (BVU Authority) – Sold to Sunset Digital 8/2018	VA	Fiber	Fiber	13124	Overbuild	2003	16,500
2733921	CBPU Telecom (Coldwater Board of Public Utilities)	MI	Fiber	Cable	312	--	2010	Businesses Only
7491137	Cedar Falls Utilities (USDA Rural Development Loan)	IA	Fiber	Fiber, Partial	995	Overbuild, Greenfield	2006	--
2295400	Chanute Utilities	KS	Fiber	Partial	575	Overbuild	2005	Businesses Only
1564186	Chelan County Public Utility District	WA	Fiber	Partial	1507	Overbuild	2004	40,000
4332102	City of Columbus	OH	Cable	--	254	--	2016	Businesses Only
1581297	City of Ellensburg	WA	Fiber	Partial	44	Overbuild	2015	Pilot Project
1824325	City of LaGrange	GA	Fiber	Partial	208	Overbuild	2000	Businesses Only
9009069	City of San Bruno	CA	Cable	Cable	326	Greenfield	2015	New Condo Development
7466642	Click! Network (Tacoma Power)	WA	Fiber	Cable	209	--	2006	Businesses Only
20641288	Community Network System (Pend Oreille County PUD) (USDA Rural Development Loan)	WA	Fiber	Partial	1986	Overbuild	2001	--
24009813	Concord Light Broadband	MA	Fiber	Fiber	520	Overbuild	2014	Residents, Businesses
17318684	Continuum (formerly MI-Connection)	NC	Fiber	Cable	108	Replace	2009	--
1717743	Conway Corporation	AR	Fiber	Cable	1429	Overbuild	2011	--
1762582	CPWS PowerNet (Columbia Power and Water Systems)	TN	Cable	Cable	685	Replace	2016	--
18582510	Douglas County Community Network (Douglas County Public Utility District)	WA	Fixed Wireless	INET	1339	Overbuild	2008	5,100
19703131	Eastern Shore of Virginia Broadband Authority (ESVBA)	VA	Fiber	--	3053	--	2016	--
18540237	EPB Fiber Optics	TN	Fiber	Fiber	6378	Overbuild	2007	165,000
8197303	EPlus Broadband (Jackson Energy Authority)	TN	Fiber	Fiber	1392	Overbuild	2004	35,000
26376368	FairlawnGig	OH	Fiber	--	6	Overbuild	2016	--
18519397	Fayetteville Public Utilities	TN	Cable	Cable	3	Replace	2010	--

[21] Source: Federal Communications Commission Form 477 from Dec. 2014, June 2015, Dec. 2016. Tech Codes: 42 (Cable Modem – DOCSIS 3.0); 50 (Optical Carrier / Fiber to the end user (Fiber to the home or business end user, does not include "fiber to the curb")); 70 (Terrestrial Fixed Wireless); BroadbandNow, Institute of Local Self-Reliance, "Community Broadband Networks Across the United States," https://broadbandnow.com/report/community-broadband-networks-across-us/ (last visited July 15, 2019); Fiberville, *Broadband Communities Magazine*, http://www.bbpmag.com/search.php (last visited July 15, 2019).

19015189	FiberNet (Monticello)	MN	Fiber	Cable	185	Overbuild	2008	--
1813369	FPUAnet Communications (Fort Pierce Utilities Authority)	FL	Fiber	Partial	18	Overbuild	2000	Businesses
18510859	Frankfort Plant Board	KY	Fiber	Cable	1211	Overbuild	2009	--
1783653	Franklin Municipal FiberNET (Franklin Electric Plant Board)	KY	Fiber	Partial	1	Overbuild	2013	Businesses; Residential Pilot
1778893	Glasgow Electric Plant Board	KY	Cable	Cable	419	--	--	Businesses Only
1621127	Glenwood Springs Community Broadband Network	CO	Fiber	Partial	53	Overbuild	2002	Businesses Only
1564350	Grant County Public Utility District	WA	Fiber	Fiber	2610	Overbuild	2000	4,300
18584425	GRUCom Fiber Optics (Gainesville Regional Utilities)	FL	Fiber	Partial	130	Overbuild	2001	Businesses, MDU, Greenfield
15753262	HES (Hopkinsville Electric System) EnergyNet	KY	Fiber	Cable	218	Overbuild	1999	--
18562652	HG&E Telecom (Holyoke Gas & Electric Department)	MA	Fiber	Partial	94	Overbuild	1997	Businesses, Some MDUs
20389763	Highland Communication Services	IL	Fiber	Fiber	238	Overbuild	2010	--
9729393	Independence Light and Power Telecommunications	IA	Fiber	Cable	27	Replace	2013	--
6186845	Lake Connections (Lake County) (USDA Rural Development Loan)	MN	Fixed Wireless	Fiber	1853	Overbuild	2010	--
4279154	MachLink (Muscatine Power & Water)	IA	Fiber	Cable	2	Replace	2015	Businesses, Expanding to Residential
2487908	Marshall Municipal Utilities	MO	Fiber	Fiber	687	--	2005	--
3715968	Murray Electric System	KY	Fiber	Cable	5	Overbuild	2000	Fiber for Businesses, HFC for Residential
6965750	Nelson County Broadband Authority (Transferring network to Central Virginia Electric Cooperative)	VA	Fiber	Partial	141	Overbuild	2015	--
18209551	NextLight (Longmont Power and Communications)	CO	Fiber	Fiber	822	Overbuild	2012	--
24024101	Ocala Utility Services	FL	Fiber	Partial	1327	Overbuild	1995	--
1564293	Okanogan County Public Utility District	WA	Fiber	Fiber	1050	Overbuild	2002	--
1783414	OMU Fibernet (Owensboro Municipal Utilities)	KY	Fiber	Partial	3033	Overbuild	1998	--
20260865	ONE Burbank (Burbank Water and Power)	CA	Fiber	Partial	49	Overbuild	2010	Businesses Only
21637632	Opelika Power Services	AL	Fiber	Fiber	435	Overbuild	2010	13,500
6993901	Optilink (Dalton Utilities)	GA	Fiber	Fiber	3131	Overbuild	2003	19,000
7096514	Osage Municipal Utilities	IA	Fiber	Cable	1	Greenfield	2016	Pilot Projects to Upgrade from Cable
4551545	Paragould Light, Water and Cable	AR	Cable	Cable	965	Replace	2017	
2871754	Parallax Systems (Richmond Power and Light)	IN	Fiber	--	499	Overbuild	2000	Businesses Only
14735781	PES Energize (Pulaski Electric System)	TN	Fiber	Fiber	7	Overbuild	2007	4,700
5221866	Reedsburg Utility Commission (USDA Rural Development Loan)	WI	Fiber	Fiber	895	Overbuild	2003	4,400 + 6,000 Rural (2010)
1783612	Russellville EPB Smartnet (Russellville Electric Plant Board)	KY	Fiber	Fiber	847	Overbuild	2010	--
24361297	Sandersville FiberLink (USDA Rural Development Loan)	GA	Fiber	Partial	34	Overbuild	--	--
5414842	Scottsboro Electric Power Board	AL	Fiber	Cable	733	Overbuild	--	Fiber for Businesses,

								HFC for Residential
23799844	Sebewaing Light and Water Department	MI	Fiber	Fiber	101	Overbuild	2013	--
9700592	Selco (Shrewsbury Electric and Cable Operations)	MA	Cable	Cable	696	Overbuild	1999	Businesses Only
21099999	Southwest Minnesota Broadband Services (SMBS)	MN	Fiber	Fiber	741	--	2010	3,700
1598457	Spanish Fork Community Network	UT	Fiber	Cable	1400	Replace	2015	--
2561884	Spencer Municipal Utilities	IA	Fiber	Fiber	427	Overbuild	2007	--
4759411	SpringNet (City Utilities of Springfield)	MO	Fiber	Partial	171	Overbuild	1997	Businesses Only
4979688	Swiftel Communications (Brookings Municipal Utilities)	SD	Fiber	Fiber	378	Overbuild	2006	--
1745603	Sylacauga Utilities Board	AL	Fiber	Cable	50	Overbuild	1997	5,000
25161969	Waverly Utilities	IA	Fiber	Fiber	285	Overbuild	2016	--
10568673	Whip City Fiber (Westfield Gas & Electric)	MA	Fiber	Partial	99	Overbuild	2015	--
1779594	Williamstown Cable & Broadband	KY	Fixed Wireless	Cable	138	Overbuild	2010	Fiber in Extension Area; Williamstown Served by HFC