The Effect of Municipal Broadband on Labor Markets: Evidence from Chattanooga, TN

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Abstract

This paper studies the causal effect of municipal broadband provision on local labor market outcomes using the introduction of a publicly owned fiber-to-the-home broadband network in Chattanooga, Tennessee. Municipal broadband networks are frequently justified as tools for economic development, yet credible evidence on their labor market impacts remains limited. I evaluate this policy using a synthetic control design that constructs a counterfactual Chattanooga from a weighted combination of comparable metropolitan statistical areas in the Southern United States that were not exposed to municipal broadband projects or public-private partnerships. The analysis focuses on the employment rate measured using the Quarterly Census of Employment and Wages (QCEW), covering the period 1991-2017. While Chattanooga's employment rate increased following the rollout of residential broadband service in 2009, placebo tests and permutation-based inference indicate that these gains are not statistically distinguishable from post-Great Recession employment growth observed in comparable cities. Overall, the results provide no evidence that Chattanooga's municipal broadband network had a significant effect on aggregate local employment. These findings contribute to the literature on broadband policy and economic development and offer cautionary guidance for policymakers considering large public investments in government-owned broadband infrastructure.

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1 Introduction

Universal broadband service is a major policy priority in the United States. The Federal Communications Commission (FCC) and Department of Agriculture (USDA) administer federal programs to subsidize or provide loans to support new broadband deployments by private Internet service providers (Nazareno and Jose 2022; Kandilov and Renkow 2010). The 2021 Infrastructure Investment and Jobs Act (IIJA) allocated $65 billion to broadband investment programs. The largest program to be established under IIJA is the $42.5 billion Broadband Equity, Access, and Deployment (BEAD) program, under which the National Telecommunications and Information Administration (NTIA) will distribute grants to all U.S. states and some territories to support broadband deployment programs, as well as initiatives to gather data that better identifies unserved and underserved regions.[1] State-level grants have not yet been awarded under BEAD, but unlike past FCC and USDA programs, the NTIA will consider awarding federal funds that support broadband networks owned and operated by city governments, rather than private Internet service providers.[2]

Many such municipal networks already exist in the U.S. As of 2011, 88 municipalities owned and operated fiber broadband networks (Yoo, Lambert, and Pfenninger 2022). A primary justification for constructing government-owned broadband networks is their expected effects on local and regional economic development. One of the most celebrated examples of a successful municipal broadband network is that built in Chattanooga, TN. EPB, Chattanooga's public electric utility, owns and operates a fiber-to-the-home (FTTH) broadband network that has serviced residents of the city and surrounding counties since September 2009. As of 2021, EPB has approximately 113,000 residential subscribers (EPB 2021), which is about 46 percent of the approximately 246,000 housing units in the Chattanooga Metropolitan Statistical Area (MSA).[3] The download speeds exceeding one-gigabit per second has earned Chattanooga the moniker "Gig City" (Marvin 2018). Despite Chattanooga's success, most municipal broadband networks fail to generate sufficient revenues to service the substantial debt used to finance the initial sunk costs associated with network deployment (Yoo, Lambert, and Pfenninger 2022). Further, previous literature has found little, albeit mixed, evidence to support positive effects of municipal broadband projects

1. See https://broadbandusa.ntia.doc.gov/funding-programs/broadband-equity-access-and-deployment-bead-program.

2. See NTIA, "Notice of Funding Opportunity: Broadband Equity, Acess, and Deployment Program," https://broadbandusa.ntia.doc.gov/sites/default/files/2022-05/BEAD%20NOFO.pdf.

3. The number of housing units is sourced from the 2021 American Community Surveys, 5-Year Estimates. The EPB service area is closely approximated by, but not equivalent to, the six counties in Tennessee and north Georgia that compose the Chattanooga MSA.

on local labor market outcomes (Guidry, Carson, and Haon 2012; Deignan 2014; Oh 2019; Ford and Seals 2021).

This study examines the effects of Chattanooga's municipal broadband network on its local labor market outcomes. Such outcomes examined by previous literature include labor force participation, unemployment rates, private-sector employment, median household income, annual payrolls, and number of business establishments (Guidry, Carson, and Haon 2012; Deignan 2014; Oh 2019; Ford and Seals 2021). Identifying the causal effect of municipal broadband on labor market outcomes is challenging because cities that choose to invest in government-owned networks differ from cities that do not in ways that affect private investment in broadband infrastructure and other, unobserved factors that correlate with labor market outcomes. In this paper, I introduce an empirical strategy that is novel in this literature–synthetic control.

Specifically, I use a pool of metropolitan statistical areas (MSAs) to construct a synthetic control that is comparable to the Chattanooga, TN-GA MSA *but for* the introduction of its municipal broadband network to residential customers in September 2009. Consistent with previous literature–particularly Ford and Seals (2021)–I find that there is no evidence to support a significant of municipal broadband on Chattanooga's overall employment rate.

This research is informative in evaluating the economic returns to large public investments in municipal broadband networks. As of May 2023, 16 states have regulations that prohibit or restrict the ability of municipalities to sell retail broadband services to their residents. Examples of such restrictions include prohibiting "overbuilding" in areas serviced by a private Internet service provider, restricting prices that can be charged to residential consumers, or requiring cities to sell their broadband services wholesale to other ISPs, rather than to residential customers directly (Cooper 2023). Chattanooga's municipal network operates under Tennessee law that allows only electric utilities to operate a broadband network within its service area.[4]

The rest of this paper proceeds as follows: Section 2 discusses previous research relevant to this question and how this research contributes to previous literature. Section 3 describes the synthetic control empirical design. Then I discuss sources of data and the selection of my control group, or "donor pool," in Section 4. I present results in Section 5, discuss their implications in Section 6, and conclude in Section 7.

4. 2021 Tennessee Code §7-59-316

2 Previous Literature

The effect of broadband on labor force participation, unemployment rates, and private-sector employment is *a priori* ambiguous because of countervailing mechanisms in the supply of and demand for labor that are affected by broadband. On the supply side, much of the previous literature has focused on the effects of broadband on labor force participation through job search. For example, Beard et al. (2012) find that broadband significantly increases labor force participation by increasing the length of time that unemployed workers search for new jobs. Other studies have considered the effects of broadband on labor force participation via increasing the availability of more flexible work arrangements, like telework. Dettling (2017) finds that married women increased their labor force participation by 4.1 percentage points when exogoneously exposed to high-speed, at-home Internet. Access to broadband at home may induce exits from labor force participation by increasing the value of time spent in leisure activities (Aguiar et al. 2021), but it may also increase labor force participation by increasing the productivity of making goods or performing services within the home (Dettling 2017). The option to shop online decreases the amount of time required to obtain goods for the home, for example.

On the demand side, the rapid diffusion of computers and other information and communications technology (ICT) led to "skill-biased" technical change that increased the relative demand of highly-educated workers with comparative advantages in cognitive, non-routine tasks relative to low-educated workers with comparative advantages in routine tasks (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). Atasoy (2013) finds broadband access causes significant increases in *employment rates* at the U.S. county level, and she finds that most of the gains in employment were attributable to incumbents increasing their scale, rather than new entry. Meanwhile, Kolko (2012) fails to reject insignificant changes in employment rates but does find evidence in support of significant increases in the *employment level*.

The way these supply-side and demand-side factors interact can produce different estimates of the net "macroeconomic" effects of broadband on labor market outcomes. In general, studies find effects not significantly different than zero or significantly positive, depending on the measure of broadband penetration used, methodology employed, the context of the empirical setting (e.g., U.S. ZIP codes, counties, states, or cross-country level analyses), or the outcome considered (relevant literature is surveyed by Kenny and Kenny, 2011 and Abrardi and Cambini, 2019).

These mixed results also extend to prior literature that studies the effects of municipal broadband on economic development indicators and local labor market outcomes. Previous papers have used matching procedures to attempt to identify causal effects. Guidry, Carson, and Haon (2012) matches 16 cities with municipal networks with 16 control cities that lack municipal networks to compare their labor market outcomes, for example. Oh (2019) uses coarsened exact matching (CEM) to reduce imbalance between regions treated by municipal broadband and control regions that are excluded from treatment. She also proposes an instrument that exogenously shifts the decision to deploy municipal broadband–the partisanship of voters in each Census place.[5] Her OLS and 2SLS estimates both fail to reject the null hypothesis that the establishment of a municipal broadband network has no effect on broadband subscription rates, unemployment rates, or labor force participation. However, use of the CEM procedure greatly reduces her sample size (and power) in the OLS specification, and the small F-statistics on her first-stage specifications (i.e., they are smaller than 10) suggest that the imprecise 2SLS results may be driven by weak instruments.

Other research has exploited exogenous variation in the timing of the establishment of municipal broadband networks to estimate the ATT via the difference-in-differences (DD) design. Most similar to my question is Ford and Seals (2021). They use a DD design to study the effects of Chattanooga's municipal broadband network on a set of labor market outcome, including labor force participation, employment rate, and wages, as well as outcomes specific to Chattanooga's industrial composition, including IT and healthcare employment. They select their control group using CEM to reduce imbalance between the controls cities and Chattanooga on observable demographic characteristics like race, sex, age, and percentage married. They fail to reject the null hypothesis that Chattanooga's municipal broadband network had a positive (or negative) effect on the city's labor market outcomes.

Deignan (2014) compares labor market outcomes in small to mid-sized cities with public fiber broadband networks (including Chattanooga) before and after network deployment against a set of "never-treated" control cities. Using the standard two-way fixed effects specification, he finds that public broadband networks have significant, positive effects on business startups and public-sector employment, negative, significant effects on worker earnings, and an insignificant effect on private sector employment. Adoption is staggered, so two-way fixed effects estimators are biased by any heterogeneity in treatment effects.

My most clear contribution is to previous literature that has estimated the causal effect of municipal broadband on labor market outcomes. To my knowledge, my paper is the first to use the synthetic control method to estimate the causal effect of a municipal

5. Oh (2019) sources her instrument from Cook's Partisan Voting Index (CVPI).

broadband network on local labor market outcomes. This method (discussed in more detail below) combines elements of matching and DD designs that have been used in the previous literature discussed above. Synthetic control is effective for conducting comparative case studies when the empiricist is interested in examining the effect of an aggregate intervention that "treats" one unit (or a small number of units) on an aggregate outcome (Abadie 2021). Further, the synthetic control design relaxes the parallel trends assumption required for identification in the DD design (Abadie 2021). I show evidence that in this setting, relaxing parallel trends is advantageous for producing unbiased estimates of the ATT.

This research also contributes to the broader literature studying the effects of broadband penetration (by private and public Internet service providers) on labor market outcomes. A variety of empirical strategies have been employed to identify the causal effect of broadband penetration on labor market outcomes. Previous studies have aimed to achieve comparability by matching areas with varying levels of broadband availability on observable characteristics (Jayakar and Park 2013; Beard et al. 2012; Alam and Mamun 2017), but the conditional independence assumption is unlikely to hold in this context.

Selection on unobservables approaches include using an instrument that varies the availability of broadband exogenously. Kolko (2012) uses slope of terrain at the U.S. ZIP code level to instrument for broadband penetration, arguing that higher-grade terrains delay broadband services relative to areas that enjoy low-grade terrains. Meanwhile, Dettling (2017) uses the share of a state's population that lives in multiple-family dwellings to instrument for the availability of high-speed, at-home Internet service. A greater share of multiple-family dwellings increases the effective population density of a state, which in turn reduces the average fixed costs associated with new network deployments. Identification of the intention-to-treat (ITT) effect requires the exclusion restriction to hold–i.e., the instrument must be uncorrelated with all unobserved factors that affect labor market outcomes. Further, the ITT is local to "compliers" who would not be exposed to broadband but for the incentive to make new broadband deployments via variation in the instrument.

An advantage of my preferred design is that I am estimating the average treatment effect on the treated (ATT). Previous papers that have estimated the ATT include Atasoy (2013), who estimates a two-way fixed effects model with a continuous treatment variable (the ratio of a county's population living in an area where broadband is available). Identification of the ATT with continous treatment requires stronger assumptions than the standard parallel trends assumption that is sufficient to identify the ATT with binary treatment (Callaway, Goodman-Bacon, and Sant'Anna 2021). Most similar to my paper, other studies use DD designs with binary treatments to exploit exogenous variation in the timing of government broadband subsidy and loan programs administered by the FCC and USDA (Kandilov and Renkow 2010; Nazareno and Jose 2022). Kandilov and Renkow (2010) find that loans administered in 2002 and 2003 under the USDA's Pilot Broadband Loan Program had significant, positive effects on employment, annual payroll, and the number of establishments in targeted areas. Nazareno and Jose (2022) find that the more recent Connect America Fund, administered by the FCC, had significant positive impacts on employment rates. This paper evaluates the efficacy of a different broadband policy: one in which government builds and operates its own broadband network, rather than subsidizing new deployments by private providers.

3 Synthetic Control Method

My empirical strategy to study the effects of Chattanooga's municipal broadband network on local labor market outcomes is to construct a synthetic control. Synthetic control is effective for conducting comparative case studies when the empiricist is interested in examining the effect of an aggregate intervention that "treats" one unit (or a small number of units) on an aggregate outcome (Abadie 2021). In my setting, there is one treated municipality (Chattanooga, TN) and many feasible control cities that form the "donor pool." In addition, there is only one treatment event–the introduction of FTTH broadband service to Chattanooga residents in September 2009. Rather than choosing the control cities *ad hoc*, synthetic control generates a "synthetic Chattanooga" by matching Chattanooga's pre-treatment outcomes with a weighted average of outcomes from cities in the donor pool.

More formally, let there be $J + 1$ units, where $j = 1$ denotes the lone treated unit, and $j = 2, \dots, J + 1$ are untreated. Let T_0 denote the last pre-treatment period. For all $t > T_0$, unit $j = 1$ is assumed exposed to treatment and all other units are assumed to be unaffected by treatment. Letting Y_{kt} denote the outcome of interest for unit k, the causal effect of the treatment in each post-treatment period $t > T_0$ is given by

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{1}$$

where $\{w_j^*\}_{j=2}^{J+1}$ is a set of optimally chosen weights such that $w_j^* \geq 0$ for all $j = 2, \dots, J+1$ and $\sum_{k=2}^{J+1} w_k^* = 1$. These restrictions on the weights prevent extrapolation beyond the support of the data that can occur in linear regression models (Abadie 2021).

The "optimality" of these weights is determined by the result of a nested optimization problem that determines balance among pre-treatment outcomes and other exogoneous predictors between the treated unit and a weighted average of the control units. Suppose there are k observable characteristics that one seeks to balance between the treated unit and its synthetic control. These "predictors" and are assumed exogenous to the treatment. In practice, predictors often include lagged (i.e., pre-treatment) values of the outcome Abadie (2021).

Let $\mathbf{X}_1$ denote the $k \times 1$ vector of predictors for the treated unit, and let $\mathbf{X}_0$ denote the $k \times J$ matrix of predictors for the control units. Let $\mathbf{W} \equiv [w_2, \ldots, w_{J+1}]'$ denote the $J \times 1$ vector of control unit weights. Given a $k \times k$ positive, semi-definite (and usually diagonal) matrix $\mathbf{V}$, the optimal weights are given by:

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sqrt{(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})} \tag{2}$$

The optimal weights $\mathbf{W}^* = [w_2^*, \ldots, w_{J+1}^*]'$ depend on $\mathbf{V}$, which can be thought of as weights on the predictors (e.g., $\mathbf{V}$ equal to the identity matrix weights all predictors uniformly). One can fix $\mathbf{V}$ according to their beliefs about the relative importance of each predictor, but in this analysis, I implement a nested optimization procedure in which an optimal $\mathbf{V}^*$ is found such that it minimizes the mean squared prediction error (MSPE) of the pre-treatment outcomes between the treated unit and a weighted average of the control units (e.g., Abadie, Diamond, and Hainmueller (2010)). Specifically, the nested optimization routine proceeds as follows:

1. Produce candidate solution $\bar{\mathbf{V}}$.

2. Find $\mathbf{W}^*(\bar{\mathbf{V}}) = [w_2^*(\bar{\mathbf{V}}), \ldots, w_{J+1}^*(\bar{\mathbf{V}})]$ that solves (2).

3. Calculate the MSPE, given by

$$\frac{1}{T_0} \sum_{t=1}^{T_0} \left[Y_{1t} - \sum_{j=2}^{J+1} w_j^*(\bar{\mathbf{V}}) Y_{jt} \right]^2$$

4. Iterate on alternative choices of $\mathbf{V}$ until one that minimizes the MSPE is found. Denote the matrix of optimal predictor weights as $\mathbf{V}^*$.

5. Retain the set of optimal unit weights $\{w_j^*(\mathbf{V}^*)\}_{j=2}^{J+1}$ to estimate the causal effect of treatment using (1).[6]

6. For similar presentation of the synthetic control method, see Abadie (2021) and Cunningham (2021)

The key identifying assumption is apparent in the subscript on the unit weights–the optimal unit weights must be time-invariant. A primary threat to this assumption is that a control unit adopts municipal broadband or another broadband policy that affects its labor market outcomes. One may also be concerned that Chattanooga's municipal network has spillovers onto other areas–perhaps by inducing migration in the surrounding areas.

Bias in synthetic control estimation depends on the size of the donor pool (J) and the number of observed pre-treatment periods (T_0). Larger donor pools increase the risk of over-fitting. Meanwhile, large T_0 reduces the bias if a set of weights can be obtained that closely balance the pre-treatment outcomes between the treated unit and its synthetic control (Abadie 2021).

4 Data

My data for labor market outcomes is sourced from the Quarterly Census of Employment and Wages (QCEW), which is published by the U.S. Bureau of Labor Statistics (BLS).[7] The QCEW reports various labor market measures at the county and MSA level, including number of establishments, monthly employment level, and average weekly wage, for all quarters from the first quarter of 1990 through the fourth quarter of 2022. The QCEW reports these measures in aggregate, across different ownership structures (e.g., private sector vs. local government), and by industry, as defined by the North American Industry Classification System (NAICS). To aggregate the monthly employment levels to a quarter measure, I simply set each quarter's employment level equal to its level in the final month of each quarter. The QCEW data are derived from quarterly, state unemployment insurance reports filed to state workforce agencies. This covers most civilian, non-farm workers, namely those who are employed by an establishment. However, the self-employed are excluded from QCEW, whereas they are not in the Current Population Survey (CPS).[8]

I construct MSA-level labor market indicators using county-level data. The QCEW reports MSA-level data from 1990 to 2012 according to the December 2003 MSA delineation file published by the U.S. Census Bureau and the Office of Management and Budget (OMB). More recent data from 2013 through 2022 is reported according to MSA definitions published in February 2013.[9] Of the 70 MSAs included in my final sample, 24 changed between

7. See U.S. Bureau of Labor Statistics, "Quarterly Census of Employment and Wages," https://www.bls.gov/cew/.

8. See U.S. Bureau of Labor Statistics, "Technical Note for the County Employment and Wages News Release," https://www.bls.gov/cew/news-release-technical-note.htm.

9. See U.S. Bureau of Labor Statistics, "QCEW Area Code Guide,"

publication of the December 2003 delineation file and publication of a revised delineation file in February 2013.[10] Estimates of the causal effect in the post-treatment periods may be biased because of these changed definitions in the QCEW file. To reduce measurement error, I use the December 2003 MSA definitions to aggregate county-level data in *all* sample periods to produce consistent MSA-level measures of labor market outcomes.[11]

I source annual population estimates from 1990 to 2022 for all U.S. counties from the U.S. Census Bureau. Intercensal population estimates are dated as of July 1 of each year. This date most closely corresponds to the last date of the second quarter in the QCEW file (June 30). Accordingly, to be consistent with my "end of period" aggregation approach with monthly measures in the QCEW, I set the second quarter population value equal to the annual intercensal estimate. I impute population estimates for Q3, Q4, and Q1 by assuming that in each county and each year, the population grew (or declined) at a constant rate. Because of my assumption that annual estimates best estimate population as of the second quarter of each year, I have county-level population estimates from 1991:1 through 2022:2.

My outcome of interest, employment rate, is defined as the sum of end-of-quarter employment levels, divided by the sum of population, across all counties belonging to a given MSA, as it is defined in the December 2003 delineation file. Employment levels are for all industries and for all ownership types, meaning private- and public-sector employment is included in my measure.

Chattanooga's municipal fiber network started serving residents in September 2009. Because of my end-of-period aggregation method for monthly employment levels in the QCEW, the quarter three measure of employment in 2009 would coincide with September 2009. Accordingly, I define the first treatment period as the third quarter of 2009, which I denote as 2009:3.

Quarterly measures of employment levels have high levels of variation within the year (perhaps due to seasonality), so to construct "smoother" estimates of the quarterly employment rate, I adjust the employment rate by constructing a four-quarter moving average. This results in the exclusion of periods 1990:2, 1990:3, 1990:4 from my sample.

https://www.bls.gov/cew/classifications/areas/area-guide.htm.

10. Three MSAs–Anderson, SC; Fort Walton Beach-Crestview-Destin, FL; and Pascagoula, MS–were eliminated as MSAs in February 2013. The other 21 MSAs were affected by having amendments made to the list of counties included in their boundary. This is unlikely wholly attributable to changes in U.S. counties. Counties change rarely.

11. Measurement error remains insofar as counties change over time. Fortunately, substantial changes to U.S. counties, defined by the U.S. Census as changes that affect the population by 200 or more, are infrequent. See U.S. Census Bureau, "Substantial Changes to Counties and County Equivalent Entities: 1970–Present," https://www.census.gov/programs-surveys/geography/technical-documentation/county-changes.html

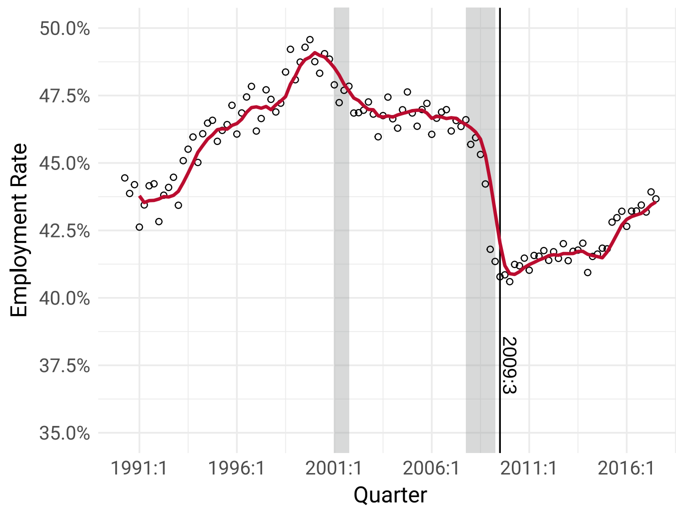


Figure 1: QCEW Estimates of Quarterly Employment Rates in Chattanooga, TN-GA
Note: The dots indicate point estimates of the quarterly employment rate; the solid line is a four-quarter moving average. The vertical dotted line indicates the quarter in which EPB began selling broadband service to Chattanooga's residents. The time periods shaded gray indicate economic recessions, as they are defined by the National Bureau of Economic Research (NBER).

Figure 1 shows how the quarterly estimates compare to the four-quarter moving average. The dots indicate point estimates of the quarterly employment rate in the Chattanooga, TN-GA MSA, and the solid line indicates its four-quarter moving average. The vertical dotted line indicates the time at which EPB began selling broadband service to Chattanooga residents. The time periods shaded gray indicate economic recessions, as they are defined by the National Bureau of Economic Research (NBER).[12]

The employment rate in the Chattanooga, TN-GA MSA fell significantly, by approximately 5 percentage points, during the 2007:4–2009:2 recession. The employment rate grew in Chattanooga following the rollout of the public broadband network; however, the introduction of the public broadband service coincides almost exactly with the trough of the Great Recession. A key question in assessing the success of Chattanooga's municipal broadband service in terms of spurring economic development is to separately identify growth in the employment rate due to EPB's fiber network from broader regional and national trends in economic recovery following the Great Recession.

To that end, I identify cities that are comparable to Chattanooga in many observable characteristics but are not affected either by Chattanooga's public network or by their own

12. National Bureau of Economic Research, "US Business Cycle Expansions and Contractions," https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

or other broadband policies. First, I identify all MSAs (as of Dec. 2003) that are in the same Census divisions as the Chattanooga, TN-GA MSA. Because the MSA crosses the Tennessee-Georgia border, the MSA lies in two Census divisions–the South Atlantic and East South Central. These two divisions are composed of the following states: Alabama, Delaware, Florida, Georgia, Kentucky, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia, as well as Washington, D.C.

Second, I source information regarding which U.S. towns and cities have engaged in municipal broadband projects or public-private partnerships from Broadband Communities, an industry publication that tracks the deployment of FTTH networks in the U.S. An Oct. 2017 report identifies 216 U.S. cities and counties in which municipal or public-private partnership projects have been engaged (Zager 2017). I use the Google Maps API to geocode most project locations to latitudinal and longitudinal coordinates. I then use shapefiles sourced from the U.S. Census to identify in which county those coordinates lie.[13] I then use the December 2003 delineation file to link those counties to their MSA, if they are assigned to one at all. When Google Maps failed to provide an accurate geolocation for the project, project locations were connected to the appropriate MSA by hand.

Third, I source annual demographic characteristics at the MSA-level from the American Community Surveys (ACS) in four pre-treatment years: 2005–2008. These demographic characteristics are percentage of the population ages 25 and older who hold a Bachelor's degree (or higher), percentage of population ages 15 and older who are married, percentage of total population that is black, percentage of total population that is male, and percentage of total population that is of prime-working age (i.e., 25–54 years old).[14] MSAs with incomplete data in these four years for any of these characteristics is excluded from the sample. I also exclude one potential donor for which there is missing county-level population data from 2014 to 2017. The affected potential donor is Lynchburg, VA. One of its member county equivalents, Bedford City, was reclassified in 2013.[16]

To summarize, to construct my set of control MSAs, I apply the following selection criteria:

13. County boundaries are as of the Jan. 1, 2000 decennial Census. See U.S. Census Bureau, "TIGER/Line Shapefiles," https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2000.html#list-tab-790442341

14. Only one-year ACS estimates are available in these periods, and one-year estimates are only published for U.S. counties with a population exceeding 65,000.[15]. Thus, I cannot aggregate county-level ACS data because not all counties that are included in my sample MSAs satisfy the population threshold for inclusion in the one-year estimates. Fortunately, measurement error associated with changing MSAs between 2003 and 2013 is not present in the 2005 to 2008 period. Amon the MSAs in my final sample, no MSA's definition was revised between December 2003 and November 2008.

16. See David Dorn, "FIPS County Code Changes," https://www.ddorn.net/data/FIPS_County_Code_Changes.pdf.

1. The MSA is in the South Atlantic or East South Central Census divisions.

2. I exclude MSAs in which a member city or county either constructed a municipal broadband network or established a public-private partnership with a fiber broadband provider.

3. I exclude potential donors for which there have any missing values of county population or demographic information sourced from the ACS from 2005–2008.

This selection procedure yields 69 control MSAs. Because I only observe municipal and public-private partnership broadband projects up to Oct. 2017, I truncate my analysis of post-treatment periods to the third quarter of 2017. In all, I have a balanced panel of 70 MSAs in 107 consecutive quarters, starting in 1991:1 and ending in 2017:3. where the third quarter of 2009 is defined as the first treatment period. In sum, I have 7,490 total observations, $J = 69$ control units, and $T_0 = 74$ pre-treatment periods.

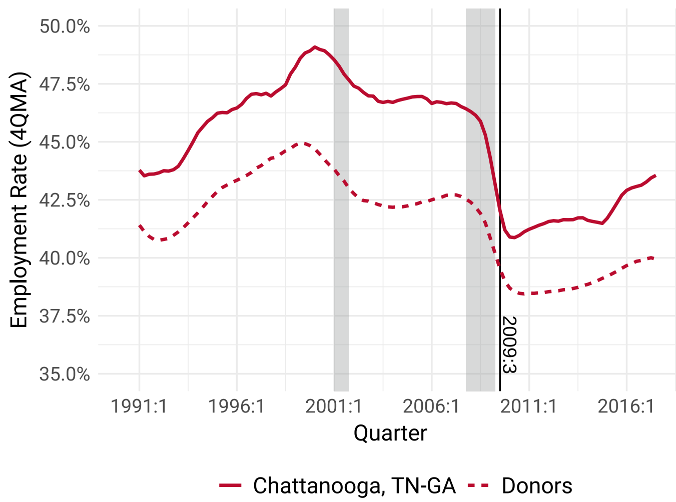
The synthetic control method described above aims to find a set of weights among the 69 donor units such that the pre-treatment trend in employment rates among donor units closely matches the levels and slope of the pre-treatment trend in Chattanooga, TN-GA. Figure 2 compares the trend in employment rates for the Chattanooga, TN-GA MSA against a simple, arithmetic average of employment rates among the 69 MSAs selected as controls. Panel 2a demonstrates that, on average, the employment rate is around 2.5 percentage points higher in Chattanooga than the donor cities.

However, panel 2b shows that the level difference is not constant throughout the sample period. If it were, this would be good suggestive evidence that the parallel trends assumption of DD holds. Instead, the employment rates of Chattanooga and donor units evolves at different rates over time. Specifically, Chattanooga appears to grow at a faster rate during the expansionary period of 1991:1 – 2000:4, and Chattanooga appears to have faced a sharper retraction in its employment rate during the Great Recession than the donor pool.

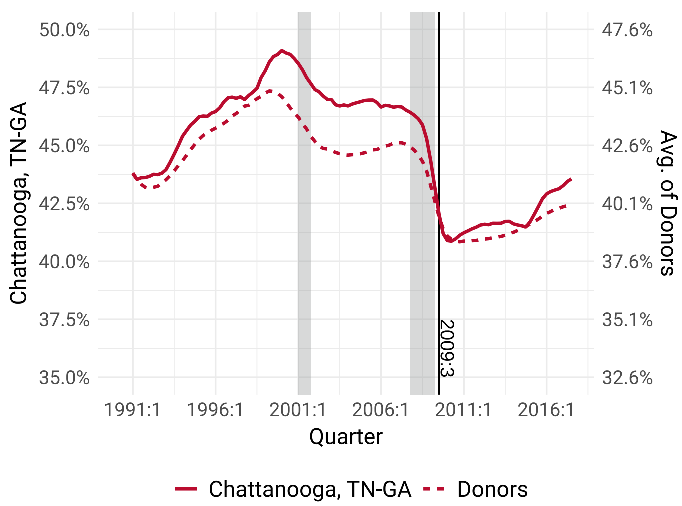
The predictors used to determine the donor weights need to achieve the following: adjust the level of the employment rate among donors to match Chattanooga's employment rates, and adjust the slopes to more closely match the changes in employment rates that are observed in Chattanooga. Accordingly, I choose the following set of predictors to generate the synthetic control:

- Average employment rate, 1991:1–2009:2.

- Annualized growth rate in the employment rate for the following periods:



(a) Unadjusted



(b) Adjusted for Level Difference in 1991:1

Figure 2: Employment Rate Trends for Treated and Control Units, 1991:1–2017:3
Note: The vertical dotted line indicates the quarter during which EPB began selling broadband service to Chattanooga residents. The time periods shaded in gray indicate economic recessions.

  - 1991:1 – 2004:4
  - 2001:1 – 2001:4
  - 2002:1 – 2007:3
  - 2007:4 – 2009:2

The first predictor can be thought of as adjusting the level of the synthetic control to match Chattanooga, and the set of four predictors under the second bullet can be thought of as adjusting the slopes of the synthetic control to match the evolution of employment rates during expansionary and recessionary periods between 1991:1 and 2009:2, which are selected according to the National Bureau of Economic Research's (NBER's) dating of the business cycle.[17]

5 Results

The five predictors described immediately above are used to generate a synthetic control for Chattanooga using the nested optimization procedure described in Section 3. All results are produced using the `tidysynth` package in the R programming language.

Figure 3 compares the trends between Chattanooga and its synthetic control. The synthetic control is much improved in fitting the levels and slopes in Chattanooga's pre-trend than is the simple, arithmetic average of the donor pool, which is shown in Figure 2a above.

Table 1 characterizes the synthetic control in terms of the predictors that were used to generate it. The first two columns confirm that the synthetic control is well-balanced with Chattanooga in terms of the levels and trends in its outcome during the pre-treatment periods. Comparison of the first and third columns shows confirms the visual intuition discussed under Figure 2a: the unweighted average of the donor pool does not match important labor market characteristics of Chattanooga in the pre-treatment period.

The average employment rate of the synthetic control matches Chattanooga's employment rate to the hundredths place and is almost 4 percentage points higher than the arithmetic average of the mean employment rates among all the control units. The annualized growth rate of the synthetic control's employment rate from 1991:1–2000:4 is almost twice that of the original donor pool average. The synthetic control is also balanced with

17. National Bureau of Economic Research, "US Business Cycle Expansions and Contractions", https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

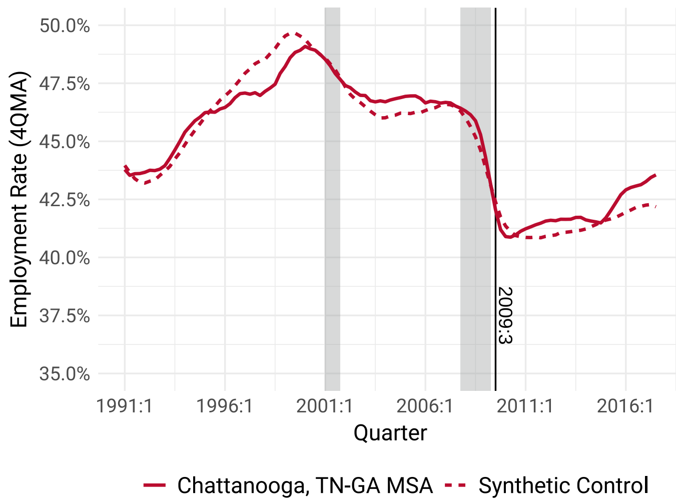


Figure 3: Trends in Employment Rates: Chattanooga and its Synthetic Control
Note: The vertical dotted line indicates the quarter during which EPB began selling broadband service to Chattanooga residents. The time periods shaded in gray indicate economic recessions.

Table 1: Synthetic Control Predictors – Balance and Weights

Variable	Chattanooga, TN-GA	Synthetic Control	Avg. of Donors	Weight
Average Employment Rate, 1991:1–2009:2	46.46	46.46	42.67	93.3
Growth Rate in Employment Rate, 1991:1–2000:4	1.02	0.99	0.59	0.1
Growth Rate in Employment Rate, 2001:1–2001:4	-1.79	-1.80	-1.86	2.1
Growth Rate in Employment Rate, 2002:1–2007:3	-0.33	-0.33	-0.04	2.8
Growth Rate in Employment Rate, 2007:4–2009:2	-4.22	-4.22	-3.28	1.7

Chattanooga with respect to its greater declines in employment rates from 2002:1–2007:3 and during the Great Recession (2007:4–2009:2).

The final column of displays the weights placed on each predictor. The optimal predictor weights minimize the MSPE in the pre-treatment employment rates between Chattanooga and its synthetic control. The predictor most effective in reducing the MSPE of the employment rate in the pre-treatment periods was the average employment rate for the entire pre-treatment sample period. This is sensible given the large, persistent gap between the employment rates of Chattanooga, TN-GA and the unweighted control group.

Table 2 shows the time-invariant weights used to generate the synthetic control. The top seven MSAs, ranked from highest-to-lowest in terms of their weights, compose 72.4 percent of the synthetic control. These seven cities include the metropolitan areas surrounding Tampa, FL; Durham, NC; Myrtle Beach, SC; Sumter, SC; Hickory, NC; Winchester, VA; and Nashville, TN. The remaining 27.6 percent is distributed across 61 of the remaining 62

Table 2: Donor Weights

MSA	Weight	MSA	Weight
Tampa-St. Petersburg-Clearwater, FL	35.9	Spartanburg, SC	0.5
Durham, NC	19.5	Virginia Beach-Norfolk-Newport News, VA-NC	0.5
Myrtle Beach-Conway-North Myrtle Beach, SC	7.1	Winston-Salem, NC	0.5
Sumter, SC	6.1	Athens-Clarke County, GA	0.4
Hickory-Lenoir-Morganton, NC	1.7	Blacksburg-Christiansburg-Radford, VA	0.4
Winchester, VA-WV	1.1	Cape Coral-Fort Myers, FL	0.4
Nashville-Davidson–Murfreesboro, TN	1.0	Decatur, AL	0.4
Gulfport-Biloxi, MS	0.8	Gadsden, AL	0.4
Harrisonburg, VA	0.8	Gainesville, GA	0.4
Charleston, WV	0.7	Goldsboro, NC	0.4
Fort Walton Beach-Crestview-Destin, FL	0.7	Jackson, MS	0.4
Raleigh-Cary, NC	0.7	Jacksonville, NC	0.4
Valdosta, GA	0.7	Macon, GA	0.4
Columbus, GA-AL	0.6	Naples-Marco Island, FL	0.4
Greenville, NC	0.6	Panama City-Lynn Haven, FL	0.4
Jacksonville, FL	0.6	Rocky Mount, NC	0.4
Knoxville, TN	0.6	Rome, GA	0.4
Savannah, GA	0.6	Tallahassee, FL	0.4
Wilmington, NC	0.6	Warner Robins, GA	0.4
Anniston-Oxford, AL	0.5	Anderson, SC	0.3
Asheville, NC	0.5	Augusta-Richmond County, GA-SC	0.3
Birmingham-Hoover, AL	0.5	Burlington, NC	0.3
Brunswick, GA	0.5	Cleveland, TN	0.3
Charleston-North Charleston, SC	0.5	Deltona-Daytona Beach-Ormond Beach, FL	0.3
Columbia, SC	0.5	Fayetteville, NC	0.3
Dothan, AL	0.5	Florence-Muscle Shoals, AL	0.3
Dover, DE	0.5	Lakeland, FL	0.3
Elizabethtown, KY	0.5	Palm Bay-Melbourne-Titusville, FL	0.3
Florence, SC	0.5	Pensacola-Ferry Pass-Brent, FL	0.3
Greenville, SC	0.5	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.3
Hagerstown-Martinsburg, MD-WV	0.5	Greensboro-High Point, NC	0.2
Hattiesburg, MS	0.5	Pascagoula, MS	0.2
Miami-Fort Lauderdale-Miami Beach, FL	0.5	Punta Gorda, FL	0.2
Mobile, AL	0.5	Lexington-Fayette, KY	0
Salisbury, MD	0.5		

control cities. This is inconsistent with the preferred property of many synthetic controls that they are sparse (Abadie, Diamond, and Hainmueller 2010; Abadie 2021). In other words, out of many donors, only a few should receive strictly positive weight.

Figure 4 shows the difference between Chattanooga's employment rate and that of its synthetic control. The synthetic control overestimates the employment rate between 1996 and 2000, in some periods by more than one percentage point. The synthetic control also underestimates the employment rate from approximately 2003 through 2007. However, synthetic control closely fits Chattanooga's employment rate in the early years of the sample period and during the Great Recession.

By (1), differences between Chattanooga and its synthetic control can be interpretted as causal effects under the identifying assumptions described above. In most post-treatment

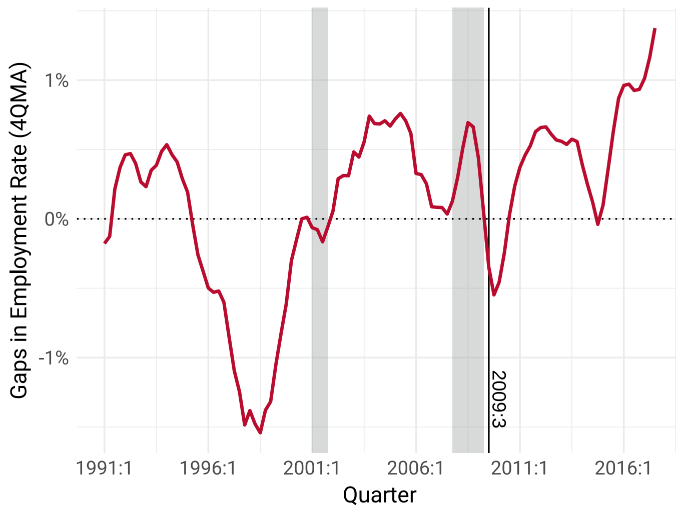


Figure 4: Differences in Employment Rates between Chattanooga and its Synthetic Control
Note: The vertical dotted line indicates the quarter during which EPB began selling broadband service to Chattanooga residents. The time periods shaded in gray indicate economic recessions.

periods, Chattanooga's employment rate exceeds that of its synthetic control, which suggests a positive effect. Further, this positive effect appears to be increasing in the number of periods after the third quarter of 2009. By 2016, the estimated effect of Chattanooga's municipal broadband network on its local employment rate is approximately 1 percentage point.

However, the significance of the estimated treatment needs to be evaluated. In synthetic control, the significance of the estimated causal effects are not tested by standard errors that are calculated under sampling uncertainty. Instead, inference in synthetic controls is done via an iterative placebo procedure (Abadie, Diamond, and Hainmueller 2010). Each MSA in the donor pool is assigned as the treated unit (and Chattanooga is categorized as a donor unit). The nested optimization procedure used to estimate synthetic controls is used for each MSA to estimate its synthetic control and the causal effect of a "placebo" treatment that occurs concurrently with the introduction of Chattanooga's municipal broadband network. If Chattanooga's estimated, positive treatment effect is significant, then one would see that its treatment effect greatly differs in magnitude from the treatment effects estimates among the control cities that received no actual treatment in the third quarter of 2009.

Figure 5 shows the results of these placebo tests. The figure excludes placebos such that the pre-treatment fit on the trend in outcomes is very poor relative to Chattanooga. Formally, if the square root of the MSPE, or RMSPE, is twice that of Chattanooga's in

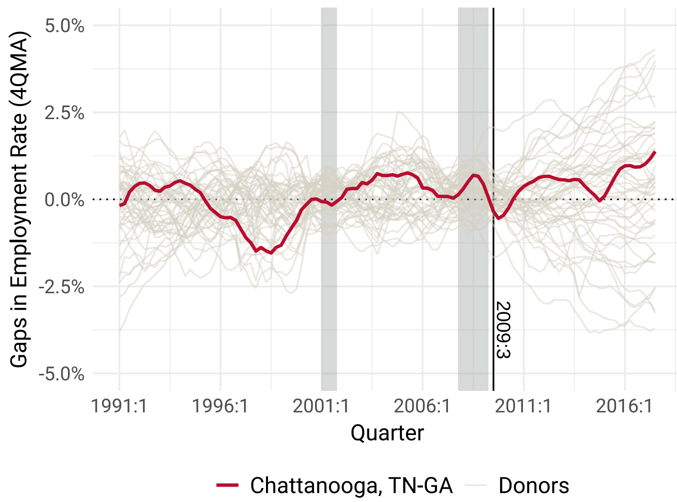


Figure 5: Employment Rate Differences in Chattanooga and Donor Cities
Note: Donors with pre-treatment RMSPE greater than two times Chattanooga's pre-treatment RMSPE are excluded from the figure.

the pre-treatment periods, the placebo is excluded from the figure. The bold, black line indicates the gaps in employment rate between Chattanooga and its synthetic control. The set of gray time series indicate the 49 placebos with satisfactory pre-treatment fit on the outcome. The post-treatment gaps in employment rate for Chattanooga fall almost in the center of the set of estimated treatment effects. Further, the estimated treatment effects for Chattanooga are much closer to zero than for many placebo cities.

More formally, significance is tested according to the treated unit's rank among all units in its estimated ratio of post-treatment to pre-treatment MSPE. All 69 controls and the treated unit are ranked from highest-to-lowest with respect to this ratio. The intuition behind the ratio is that when treatment effects are significant, the synthetic control will poorly fit the observed trend in post-treatment outcomes, increasing the numerator. Meanwhile, if the synthetic control is well-fit to the pre-treatment data, then the MSPE of pre-treatment outcomes is low, decreasing the numerator. Hence, the ratio of post-to-pre MSPE increases.

Figure 6 shows Chattanooga's ratio of MSPEs and its rank relative to the 69 cities in the donor pool. It is clear that Chattanooga's MSPE ratio is dissimilar to most MSPE ratios computed in the iterative placebo tests.

Table 3 shows Chattanooga's post-MSPE to pre-MSPE ratio is 1.08, meaning that the synthetic control only does slightly worse at predicting its employment rate after the introduction of its municipal, residental broadband network. This ratio ranks 42/70 overall. If Chattanooga's municipal broadband network had a significant effect different than zero,

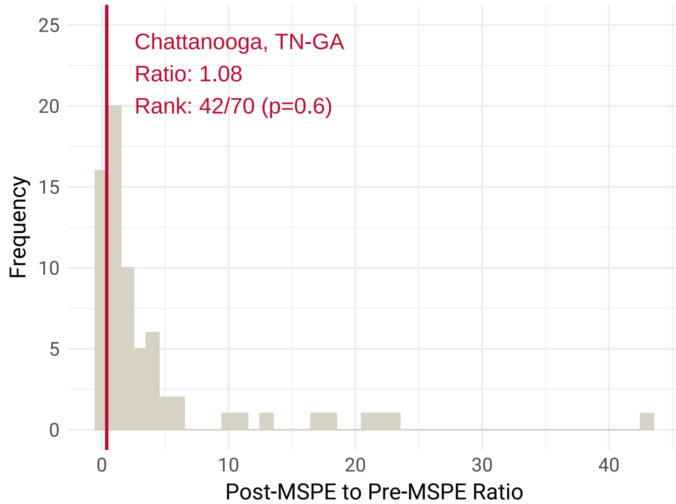


Figure 6: Distribution of Post-Pre MSPE Ratios

Dependent Variable	Employment Rate
Ratio Post-Pre MSPE	1.08
Rank	42/70
p-value	0.6

Table 3: Chattanooga's Post-Pre MSPE Ratio

we would expect this ranking to be near or equal to 1. The p-value calculated using Chattanooga's rank is 0.6, meaning that if Chattanooga's treatment effect were actually equal to zero, then there's a 60 percent probability that a rank of 42 out of 70 would be observed under these placebo tests.

6 Discussion

Consistent with Ford and Seals (2021), I fail to reject the null hypothesis that the introduction of Chattanooga's public fiber broadband service to its residents had a significant effect on its overall employment rate. The fact that Chattanooga's employment rate grew in the quarters and years following the introduction of the municipal broadband network in September 2009 is not distinguishable from growth in employment rates in the years following the Great Recession among comparable cities in the Southern United States.

I discuss limitations to my analysis. The fit of the synthetic control to the observed pre-treatment employment rates in Chattanooga is worse than in prior synthetic control papers (e.g., Abadie, Diamond, and Hainmueller (2010)). Further, Table 4 shows that in terms of demographic observables that are usually controlled for in studies related to broadband deployment and labor market outcomes, the synthetic control is not balanced with Chattanooga's demographic characteristics. In particular, the synthetic control has a greater share of black and Hispanic people, and its adults are more educated. Almost 6 percent more adults ages 25 and over hold at least a Bachelor's degree in the synthetic

Table 4: Balance Table – Demographic Characteristics

Variable	Chattanooga, TN-GA	Synthetic Control
% Prime-Age Workers (25–54)	42.06	41.80
% Male, All Ages	48.21	48.66
% Black, All Ages	13.91	19.33
% Hispanic, All Ages	2.18	9.07
% Bachelor's (or higher), Ages 25+	21.80	27.10
% Married, Ages 15+	53.25	50.09

Note:
The estimates presented are averages for annual values from 2005–2008. Averages for the synthetic control are weighted by the donor weights. Source: Author's calculation; American Community Surveys, 2005–2008

control. People are more likely to be married in Chattanooga, relative to its synthetic control.

Table 1 shows that the predictor most effective in minimizing the MSPE was the average employment rate over the entire pre-treatment period. An alternative method proposed by Arkhangelsky et al. (2021) may be able to estimate the treatment effects of Chattanooga's broadband network without requiring a weighted average of the control units to match Chattanooga's employment rate level closely. Instead, their synthetic DD method only requires that a set of control unit and time weights be able to satisfy the parallel trends assumption.

Further, the synthetic control is not sparse–69 of the 70 control MSAs contribute strictly positive weight to the synthetic control. Both indicate that my results may be biased (Abadie 2021). Regularization methods that penalize synthetic controls that use many donors or many predictors may help assuage this source of potential bias (Abadie 2021).

A key threat to identification is that a member of the donor pool is exposed to similar policy treatments as Chattanooga. I excluded MSAs in the Southern U.S. where any part of it had been affected by either the introduction of a municipal broadband network or a public-private partnership, according to Zager (2017). Further refinements could be made to the donor pool. For example, the Universal Service Administration Corporation (USAC) publishes data that identifies which U.S. Census blocks (and thus U.S. counties and MSAs) that have received broadband deployments subsidized by the U.S. Federal Communications Commission's (FCC) Universal Service Funds programs.

7 Conclusion

In this paper, I analyzed of the effects of Chattanooga's municipal broadband network on a primary local labor market indicator–the overall employment rate. This paper contributes an empirical design novel to this literature–synthetic control. I find no evidence via the synthetic control design that the network had any significant effect on its overall employment rate. Instead, the fact that Chattanooga's employment rate grew in the quarters and years following the introduction of the municipal broadband network in September 2009 is not distinguishable from growth in employment rates in the years following the Great Recession among comparable cities in the Southern United States.

U.S local, state, and federal policy in the past decade has been oriented towards facilitating the construction of government-owned, municipal broadband networks. Insofar as this and past research has failed to demonstrate the effectiveness of these public networks in achieving their stated economic development goals, claims that such policy reforms would have significant economic effects ought to be qualified or nuanced.

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