The Last Mile of Broadband: Estimating the Economic Impacts of Connect America Fund Initiative

By

Zanele Munyikwa

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Authored by: Zanele Munyikwa
MIT Sloan School of Management
January 30, 2023

Certified by: John J. Horton
Richard S. Leghorn (1939) Career Development Professor
Associate Professor, Information Technology
Thesis Supervisor

Accepted by: Eric So
Sloan Distinguished Professor of Financial Economics
Professor, Accounting and Finance
Faculty Chair, MIT Sloan PhD Program

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Abstract

I use a county-level panel dataset from 2013 to 2019 to assess the impacts of a federal program that provided massive subsidies to facilitate the expansion of broadband infrastructure: The Connect America Fund Phase II Program. This program incentivized telecommunications carriers to provided broadband access to high-cost areas in the United States (typically rural and other underserved communities). I study the impact of this "last mile" of broadband and assessing broadband access on local economic employment outcomes. I find that program funding in a geographic area has a positive effect on weekly wages, and potentially has a positive impact on population development.

Thesis supervisor: John J. Horton
Title: Associate Professor, Information Technology, Richard S. Leghorn (1939) Career Development Professor at the MIT Sloan School of Management

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1 Introduction

Economists, information systems researchers and policymakers are keenly interested in understanding the productivity and labor market effects of the advancements in information and communication technology (ICT). Particular emphasis has been placed on tech as a uniquely important catalyst for regional economic development, particularly in rural and underresourced areas.

One critical technology that researchers have studied is high-speed broadband. Broadband internet is critical to the functioning of our modern world. The provision of broadband services is essential for economic success in the United States, as well as in other countries (DeStefano et al., 2018; Briglauer and Gugler, 2019; Guriev et al., 2020). It enables the rapid transfer of large amounts of data at high speed, making it the backbone of many industries. It facilitates communication, collaboration, research and development, and allows people access to the wealth of information available on the internet. Importantly, prior research has found that the contribution of broadband internet to employment has three simultaneous effects: the impact on company productivity (DeStefano et al., 2018), the impact on macroeconomic productivity through e-business, and the increase in employment opportunities (Katz, 2012).

Others have questioned this optimistic view– there are mixed findings when surveying prior research on the impacts of broadband access on economic productivity and labor market outcomes. While rapid technological innovation can boost economic growth, it can also further economic inequality–creating a system of haves and have-nots. Research focusing on broadbands unequal benefits has identified that there are heterogeneous effects based on skill, organization seniority, gender, and race (Almeida et al., 2017; Poliquin, 2020; Akerman et al., 2015). In this paper, I focus on one potential attribute, the rural vs urban geography of a county. Given the concentration of routine manual work in rural regions in the United States, there remain questions about whether the positive benefits from broadband will extend to rural areas, and for which employees/individuals. Motivated by this debate, in this study, I use the natural experiment of a federal broadband program to study the impact of broadband access on under-served rural areas.

The majority of prior research on the economic impacts of broadband has focused on the rollout of broadband between 2000-2012. During this time, there was a rapid increase in broadband infrastructure and rollout in the United States. However, there is a significant disparity in the spatial distribution of broadband services globally, with rural areas often lagging behind urban ones (Grubesic, 2008). After the initial roll-out of broadband, in 2015, over 50% of rural Americans lacked access to broadband (Tomer et al., 2017). This lack of access to broadband has a negative impact, particularly in impoverished and less developed regions of the United States (Kolko, 2010). Motivated by the unequal to access that persisted in the United States, and the economic benefit that broadband has been shown to have in rural areas, federal, state and municipal governments have implemented policies to expand access and cover "the last mile of broadband." In this paper, I examine the impact of one of these programs.

The program I study in this paper is the Connect America Fund program. The Federal Communication Commission (FCC) Connect America Fund program has provided over $10 billion over the past six years to close the rural-urban broadband gap. In this paper, I extend the existing research about to assess the impact of broadband access on economic outcomes with a focus on local (county-level) employment outcomes. I ask whether a federal policy designed to close the broadband digital divide resulted in a positive impact on rural/underserved counties economic output and labor market outcomes? Why or why not?

Through a descriptive analysis of the impact of the program and a difference in differences model of counties included in the federal program, I examine whether federal funding to incentivize broadband resulted in installations of broadband in and whether this funding led to positive employment outcomes for those regions. The main findings are that financial support to counties in the program lead to higher average wages, increased employment levels, and increased number of establishments employing individuals. I also find that these gains are largest for the counties which have higher employment in tech-intensive industries before the program.

This thesis is divided into eight sections which are structured as follows. Section 2 assesses the current evidence on the impact of broadband on productivity and local labor markets. Sections 3 and 4 describe the empirical setting further. Section 5 verifies that the program intervention resulted in the deployment of broadband to underserved areas. In Sections 6, I describe the empirical strategy for causal identification of the impact of the program on employment outcomes. I then present results in Section 7. Section 8 concludes with a discussion of the results and exploration of implications of the findings. I close with areas for further research.

2 Literature Review

In this literature review, I will discuss the prior research on the impact of broadband access on economic outcomes, the digital divide in terms of broadband access, and the impact of broadband on inequality and unequal benefits to broadband.

2.1 Impact of Broadband Access on Economic Outcomes

Broadband is a term that refers to high-speed internet access that is consistently available and faster than traditional dial-up access. It encompasses a range of high-speed transmission technologies.[1] The internet, particularly broadband access, has become a crucial element of the global economy. .

Broadband has been vital for the digital transformation of our society and the economy over the past two decades; the proliferation of broadband access has led to numerous changes in individuals' social activities, including how they work and study. For example, there has been an expansion of on educational programs offered over the internet. The impact of broadband on education has been significant, particularly in terms of the abundance

[1] `https://www.fcc.gov/general/types-broadband-connections`

of educational programs and the wealth of content that is shared online, hence fostering globalization, new educational methods, and student mobility. In turn, broadband technologies have contributed to the pressure on higher education institutions to adapt to rapid social, economic, and technological changes. In this context, lifelong learning is becoming both available and increasingly important, supporting the development of the most relevant skillset required by the U.S. economy, vis-à-vis the new opportunities for online distance learning (Dettling et al., 2018). Additionally, the growth of remote work has made it a more practical option for both employees and businesses. For instance, certain medical services can be outsourced online, potentially providing cost savings for rural populations. Moreover, rural businesses are increasingly adopting e-commerce and internet practices, leading to increased economic vitality and expanded market reach (Stenberg et al., 2010). The COVID-19 pandemic made broadband even more important for access to education, work, and social support—Katz et al. (2020) finds that digitization (in the form of broadband access) mitigated some of the disruption caused by the pandemic.

A growing body of evidence indicates that there are increasing economic returns to broadband expansion in terms of economic growth(Kolko, 2010). Greenstein and McDevitt (2009), among other work, conceptualizes internet as a general purpose technology (GPT). Bresnahan and Trajtenberg Bresnahan and Trajtenberg (1995) define a GPT as a technology whose adaptation to a variety of circumstances raises the marginal returns to inventive activity in each of these circumstances—these technologies are "engines of economic growth". Previous research has demonstrated the impact of broadband technology on Gross Domestic Product (GDP) growth, although data on the specific impact varies (Holt and Jamison, 2009; Katz, 2012; Rohman and Bohlin, 2012). Alper and Miktus (2019) describe the impact of digital connectivity on economic growth and development in Sub-Saharan Africa and denote the potential to drive economic growth and development in the region with broadband services (see also Cariolle et al., 2018).

Studies from various countries, including the U.S., have shown that the one factor in the positive economic benefits of building a broadband are the impacts of labor productivity (Whitacre et al., 2014; Gonzales, 2016; Oh, 2019). According to Bhuller et al. (2019), the availability of broadband access has led to a significant increase in the use of online job searches and employment. Data indicates that broadband access significantly enhances the process of searching for a job, with the average duration of a vacant position decreasing by 9% and the share of companies experiencing recruitment problems falling by 13%. It is possible that access to information on open positions may have further reduced the natural rate of unemployment. According to the data, a stable unemployment rate could potentially be increased by 25% if there were no access to broadband services. In addition, the presence of broadband services has caused significant changes in the labor markets in the United States and other countries. These changes include an increase in the representation of women in the workforce (Black and Spitz-Oener, 2010; Suhaida et al., 2013), higher wages, and a faster rate at which job offers are filled (Forman et al., 2012; Atasoy, 2013).

The study in Briglauer et al. (2019) is the most closely related to the subject of this paper–it examines at the impact of broadband policy for rural areas on employment outcomes, but in Germany rather than the United States. They find that policies aimed at increasing broadband coverage through state subsidies have the potential to incentivize productive individuals to enter the labor market. This finding is supported by other studies outcomes that examine the impact of broadband on individuals' labor market outcomes—for example, access to rapid internet services has led to increased participation of married women, particularly those who are college-educated with children, in the workforce (Dettling, 2017). Importantly, in addition to the finding on incentivizing individuals to enter the job market, Briglauer et al. (2019) find that an increase in broadband coverage through state aid prevents rural areas from depopulation, but does not contribute to a further closing of the economic divide in the form of creating new jobs.

2.2 Broadband and the Digital Divide

There remains global goal to promote widespread, high-quality broadband access, as it has been shown to contribute to a more prosperous society. There is a significant disparity in the spatial distribution of broadband services globally, with rural areas often lagging urban ones (Grubesic, 2008). This type of distribution issue is not unique to major powers but occurs in many regions worldwide. Holt and Jamison (2009) examined the connection between information and communication technologies and economic growth and found that accessibility still favors urban areas. Research has shown that countries that expanded broadband services, perform well on average in terms of accessibility and quality, but lag in infrastructure, internet use, and knowledge (Cariolle, 2018). On the one hand, there has been a significant increase in internet expansion, while on the other hand, the country's exposure to interruptions and digital isolation - reducing internet and mobile telephony penetration rates, reducing investments in ICT, increasing mobile phone tariffs, and fixed network instability (Whitacre and Gallardo, 2020).

These findings suggest that difficulties in maintaining access to broadband services are often correlated with poor health, unemployment, and other negative social and economic phenomena, indicating that technology maintenance is reflective of broader inequality issues (Gilbert, 2010; Gonzales, 2016).

2.3 Heterogeneous Returns to Broadband Access and Impacts on Inequality

Prior work has found evidence of skill-biased technological change over the past 20 years. the introduction of technology has increased the demand for more-skilled labor relative to less-skilled labor at fixed relative wages. Some argue that ICT leads to increased productivity, while others worry that it may lead to job losses and reduced wages. Exacerbating this trend, the same artificial intelligence (AI) technologies that augment high-wage cognitive employment are more abundant in large cities, while the physical low-wage tasks that are most readily replaced by robotics are more abundant in small cities and rural communities. While earlier work on automation and skill-biased technical change has shown that technologies are more prone to replace routine work (Autor et al., 2003), recent evidence also suggests that the displacement of middle-skilled labor has accelerated since the early 2000s (Bessen et al., 2020). Although the decline of middle-skilled work has been attributed to international trade, geographic polarization of the urban-rural divide, and structural changes in the economy, another main factor driving these changes in the last two decades is the use of a new wave of automation technologies (Acemoglu and Restrepo, 2018; Autor et al., 2006, 2019).

As discussed in Almeida et al. (2017), there is widespread concern about the displacement of lower-skilled workers due to the increasing automation of routine and manual tasks through technology. Studies have shown that after a technological shock, technology-intensive industries tend to reduce their reliance on both skilled and unskilled labor, but the decline in employment is typically more significant for unskilled tasks. This shift in the workforce towards non-routine, cognitive skills has led to the development of labor policies that specifically benefit these workers. In addition, research by Akerman et al. (2015) has investigated the relationship between broadband access and labor productivity and wages. They found that providing broadband access to companies can improve the productivity and work results of qualified workers and that it can also complement skilled workers in performing non-routine abstract tasks while replacing unskilled workers in routine tasks, which potentially could increase the wage gap.

Poliquin (2020) finds that there is a discrepancy in the benefits experienced by employees at different levels within an organization following the adoption of broadband. Specifically, it was found that wage inequality among managers increased while inequality among workers either decreased or remained unchanged. These findings have led to the recognition of the impact of broadband access on the labor market as a significant political issue, particularly in discussions surrounding incentives for broadband internet access. The study also found that the transition from non-availability to full availability of broadband signals resulted in an increase of 1.8% in the employment rate, with a greater effect being observed in rural and isolated areas. Additionally, it was noted that broadband technology complements skilled labor, leading to an increase in the relative demand for skilled labor upon expansion.

Moreover, Forman et al. (2012) found that investments in advanced internet infrastructure are associated with significant wage and employment growth in areas with concentrated IT use, high income, large populations, and high skills. However, it should also be noted that widespread access to broadband has exacerbated regional income inequality (Forman et al., 2012). However, Mack et al. (2019) argue that it is necessary to conduct more in-depth analyses of the ways in which broadband data benefits society. As broadband access continues to be a crucial aspect of our society, particularly considering the COVID-19 pandemic, policy efforts continue to shift towards increasing the availability and adoption of high-speed internet technology (Katz et al., 2020).

3 Setting

In this paper, I discuss the effects of a two-part federal program by the Federal Communications Commission (FCC) which rolled out from 2012-2020. The Connect America Fund (CAF) is a program created by the Federal Communications Commission (FCC) in 2011 that helps to reduce the cost of bringing voice and broadband services to rural, underserved, and high-cost areas in the United States. The fund is administered through the Universal Service Administrative Company (USAC). Companies that are eligible to receive funding are typically eligible telecommunications carriers (ETCs) or rural service providers. The program also provides support to carriers that are eligible to receive support from the High-Cost program. The goal of this program was to supply funds to qualified telecom companies under the condition that would commit to build broadband infrastructure in unserved areas. In 2012 and 2014, the FCCs Connect America Fund (CAF) awarded \$400 million dollars. The Phase II of the CAF program provided an additional \$1.5 billion in 2018 through a series of reverse auctions. on the condition that carriers service additional unserved areas by 2020.

In this section, I describe the key features of the program.

3.1 Program Origin and Purpose

The program was designed to ensure that consumers in rural and high-cost areas have access to modern communications networks capable of providing voice and broadband service at rates that are reasonably comparable to those in urban areas. The Connect America Fund provides funding to telecom carriers to provide service in rural areas where the market alone cannot support the substantial cost of deploying network infrastructure and providing connectivity. The program furthers this universal service goal by allowing eligible carriers who serve these areas to recover some of their costs from the federal Universal Service Fund. Under the umbrella of the High Cost Program, the Connect America Fund administers several programs:

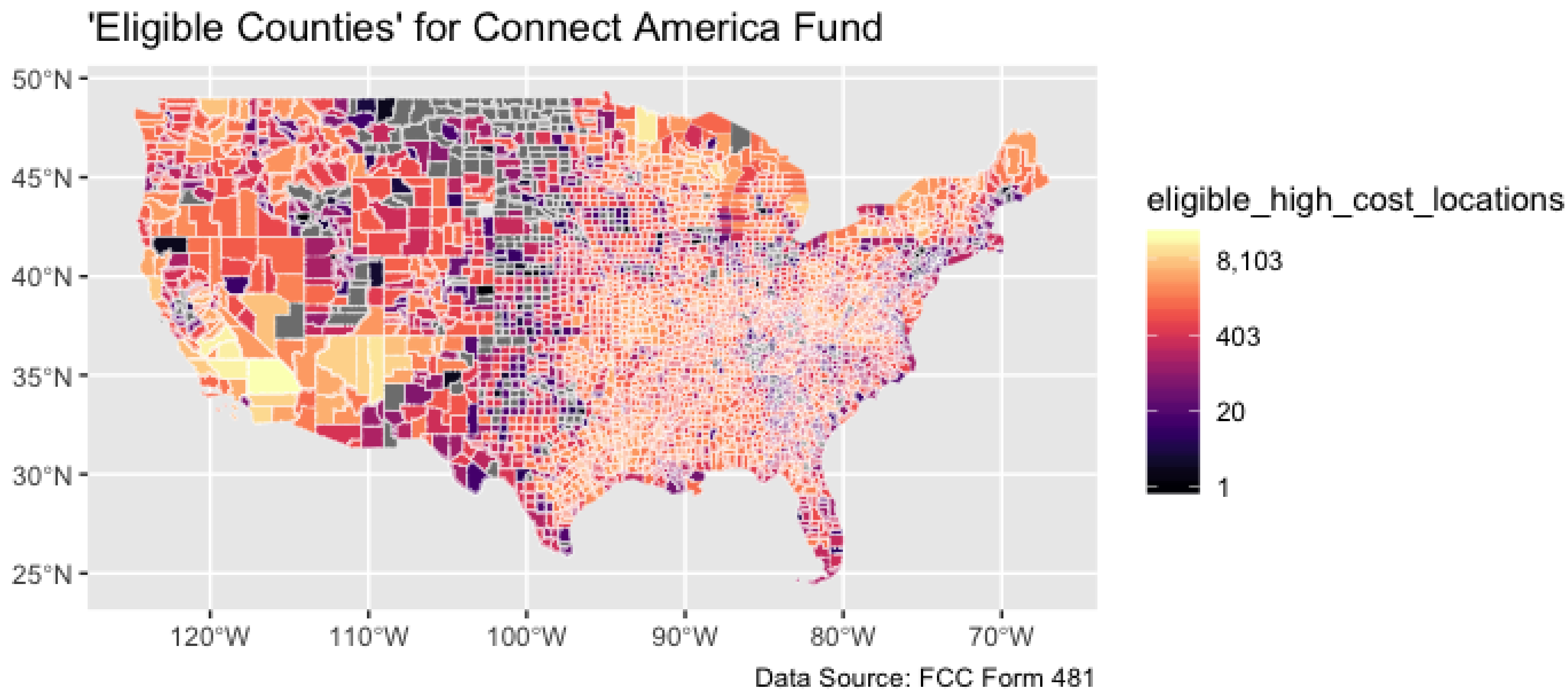
1. Rural Broadband Experiments (RBE)
2. ACAM
3. AK Plan
4. CAF-II Cost Model
5. CAF-II Auction
6. CAF-BLS.

In this paper, I focus on the components with the largest funding and impact: 1, 3, and 5. For more details on the other program, see Appendix A.

3.2 Program Eligibility Determination

At the outset of the Connect America Fund, the Federal Communications Commission (FCC) used December 2016 Form 477 data in order to identify Census Blocks in the US underserved by broadband service providers at speeds of 10/1 Mbps. Census blocks are "statistical areas bounded by visible features such as roads, streams, and railroad tracks, and by non-visible boundaries such as property lines, city, township, school district, county limits and short line-of-sight extensions of roads...Generally small in area. In a city, a census block looks like a city block bounded on all sides by streets. Census blocks in suburban and rural areas may be large, irregular, and bounded by a variety of features, such as roads, streams, and transmission." In addition to this, the FCC considered variables including population density, geography and regional labor costs in deciding on a list of eligible census blocks and the amount of financial support on offer for each. The data released by the FCC in 2014 lists each eligible census block, the number of eligible high cost locations (residences or businesses) and the number of eligible extremely high cost locations. I aggregate this up to the county level, and the below map shows counties and the number of eligible locations in each. Figure 1 depicts the eligible counties. Table 1 shows summary statistics on the demographics of these eligible counties.

Figure 1: CAF-II Program Eligible High Cost Locations by County



Notes: This figure depicts a map of the United States with shading according to the number of eligible high cost locations in a given county. The model to deterine the number of eligible high cost locations is based on data from the FCC's Form 481, which is filled out by telecom carriers in the program

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
High Cost Locations	1,123.41	1,405.51	1	181.8	688	1,636	19,358
Extremely High Cost Locations	136.52	233.65	0	14	61.5	184	3,956
Eligible Tracts	6.35	6.82	1	3	5	8	83
Total Population	101,535.90	322,472.70	73	13,317	28,463	70,618.5	9,974,203
Percent Male	0.50	0.02	0.37	0.49	0.49	0.50	0.72
Households	37,488.32	112,437.20	33	5,117.5	10,830	26,762.8	3,242,391
Commute to Work	23.49	5.39	5	20	23	27	43
Population Density	273.67	1,780.98	0.04	20.94	49.68	136.76	71,434.09
Median Household Income	48,467.93	13,388.93	11,201	40,233.2	47,111	54,704.2	131,618
Unemployment Rate	0.09	0.04	0.00	0.06	0.09	0.11	0.34
Percent Black	0.09	0.15	0.00	0.01	0.03	0.11	0.86

Notes: This table provides overall summary statistics of the main dataset. Data is at the county level. *Eligible High Cost Locations* and *Extremely high cost locations* are continuous variables sourced from FCC data on the Program Eligibility results before the auction. *N_tracts* is a measurement of the total number of tracts in the county that have eligible census blocks according to the number of eligible high cost locations in the block. *Total population* is the population according to the 2010 Census in a given county. *Percent Male* describes the percent of people in the population in the county who are male. *Households* is similar to population but measures the number of household units, rather than individuals. *Commute to work* is a measure of the average number of miles individuals must commute to work, and is a valuable measure of the rural/urbanness/economic development of a county. *Population Density* is the measure of the is a measure of average population per square mile. *Percent Male Households Commute to Work Population Density*, *Median Household Income*, *Unemployment Rate* and *Percent Black* are all sourced from the American Community Survey in 2013 (prior to the start deployment of the program)

3.3 Program Process

Here, I briefly describe the timeline of the programs and the salient details of the process.

The Rural Broadband Experiments were designed to advance the deployment of next-generation networks to areas unserved by an unsubsidized competitor as quickly and efficiently as possible and to understand how the Phase II Auction should be structured. Proposals were submitted by carriers, and the FCC chose recipients based on those proposals. The reverse auction is a second price auction--which means that the lowest bidder wins the auction, but they will receive support equal to the second-lowest bid. The rural broadband experiments program (RBE) paved the way for the auction portion of the CAF. After allocating funding via RBE, there was an initial opening for 'price cap' carriers to opt into a subsidized incentive plan. These amounts were determined by the use of a complicated and compelx cost calculation algorithm ('cost model') that aimed to calculate the cost of providing service in every part of the country.

In 2015, ten price cap carriers accepted an offer of Phase II support calculated by this model in exchange for deploying and maintaining voice and broadband service in the high-cost areas in areas where they had accepted offers. The areas for which price cap carriers did not accept model-based support, as well as other areas, were made available in the CAF Phase II auction.

Figure 2 summarizes this timeline.

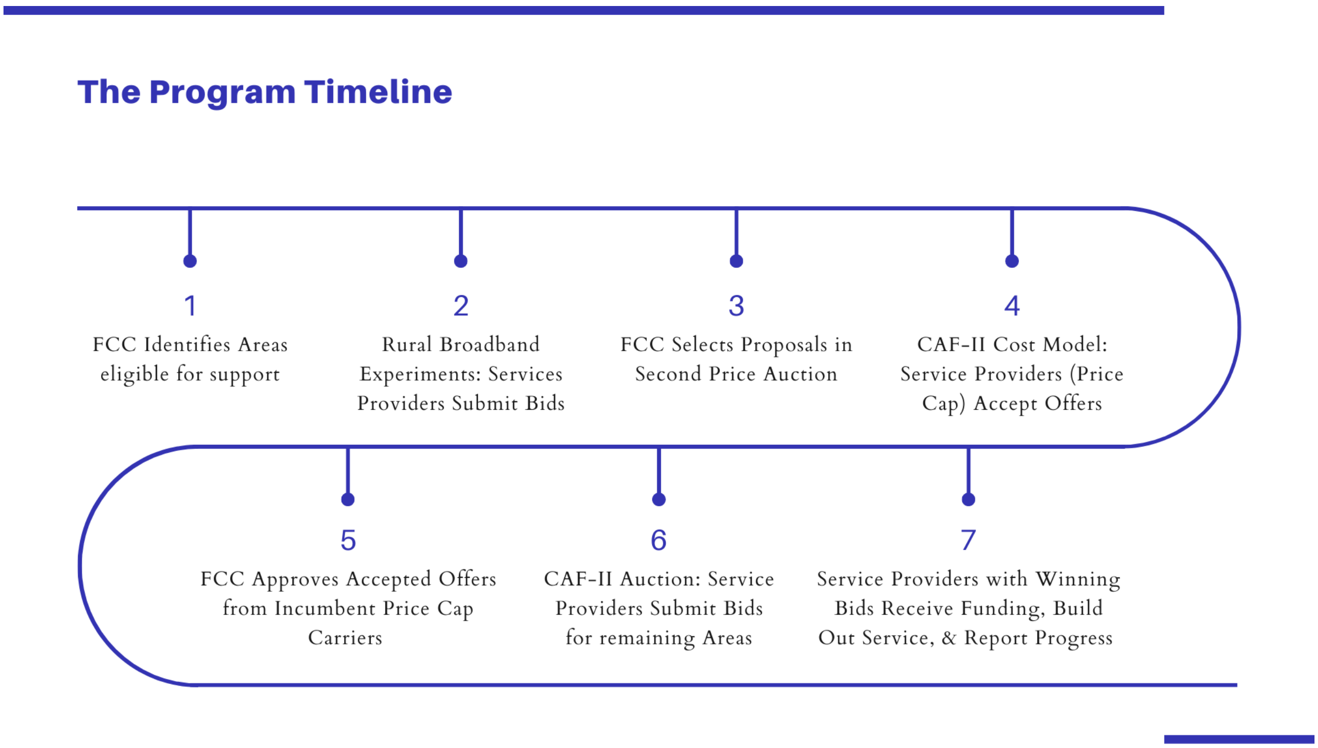
4 Data

My outcome data comes from the following sources:

4.1 The Federal Communication Commission (FCC)

The Universal Service Access Fund organization created a High Cost Universal Broadband portal (HUBB). This is a data management portal where location data will is filed for

Figure 2: Connect America Fund Program Timeline



recipients of ACAM, CAF-II, CAF-BLS and RBE. This includes high-level information from the required form for High Cost program providers to file annually, the Form 481. From this data, I get construct a panel dataset on each installation, the latitude and longitude, the carrier, and which program it corresponds to (RBE & CAF-II only). I match the latitude and longitude to the eligible county. Additionally, I use the FCC listed the 30,033 CBGs eligible for the auction, along with their IDs, the number of locations, and the reserve prices, and the total annual support allocated to the winning bidders.

4.2 Bureau of Labor Statistics: Quarterly Census of Employment and Wages

The Quarterly Census of Employment and Wages (QCEW) is a data collection program that is managed by the Bureau of Labor Statistics. This program publishes a quarterly counts of establishments, employment by industry, and wages, and unemployment reported by employers and is built from State-submitted Unemployment Insurance (UI) records. These records are linked and provide a time series of employment and wage outcomes. QCEW is comprehensive, capturing 98% of U.S. wage-and-salary jobs.

4.3 Bureau of Economic Analysis: Regional Data

BEA regional data consists of a range of economic indicators collected and published by the US Bureau of Economic Analysis (BEA). These indicators cover everything from personal income to employment and wages at the regional level. The data is broken down by state, county, metropolitan area, and other subregional levels. This data provides a detailed picture of regional economic performance and can help inform economic policy decisions.

4.4 American Community Survey

The American Community Survey (ACS) is an ongoing survey prepared by the U.S. Census Bureau. The Census Bureau selects a monthly random sample of addresses to be included in the American Community Survey. Each address has about a 1-in-480 chance of being selected in a given month, and no address should be selected more than once every five years. They release 1-year estimates and 5-year estimates (and until 2013, 3-year estimates).

For one-year estimates, these are composed of 12 months of collected data and are restricted to data for areas with populations of 65,000 + people. I use these 1-year estimates for the model estimation. For the summary statistics I report in the eligibility section, I report data from the 5-year estimates, which cover all the counties in the U.S.

5 Program Impact: Was the program successful?

This paper utilizes a unique setting—this program is the first of its kind in the United States. However, the primary purpose of this paper is not to evaluate the program's impact or to identify whether the program was a 'success', but I briefly discuss this topic in this section.

For our purposes, the main key finding from Glass and Tardiff (2019) is what's important—although the auction was risky and weedy in details, it worked. The auction lowered the cost of providing broadband service in unserved areas by attracting new providers." The program impact can be discussed in terms of multiple important variables and outcomes–in this paper we focus on total installations and annual support allocated.

Prior work, such as Glass and Tardiff (2019) evaluates the impact of the program and examines the dynamics involved in a reverse auction. Namely, they find that the auction in the CAF-II program attracted new providers, widened the service quality offerings, and lowered costs below the reserve prices estimated by cost model designed for the program.

Here, we display some preliminary analysis of the impact of the program as it pertains to our core research question, but further examination of the outcomes.

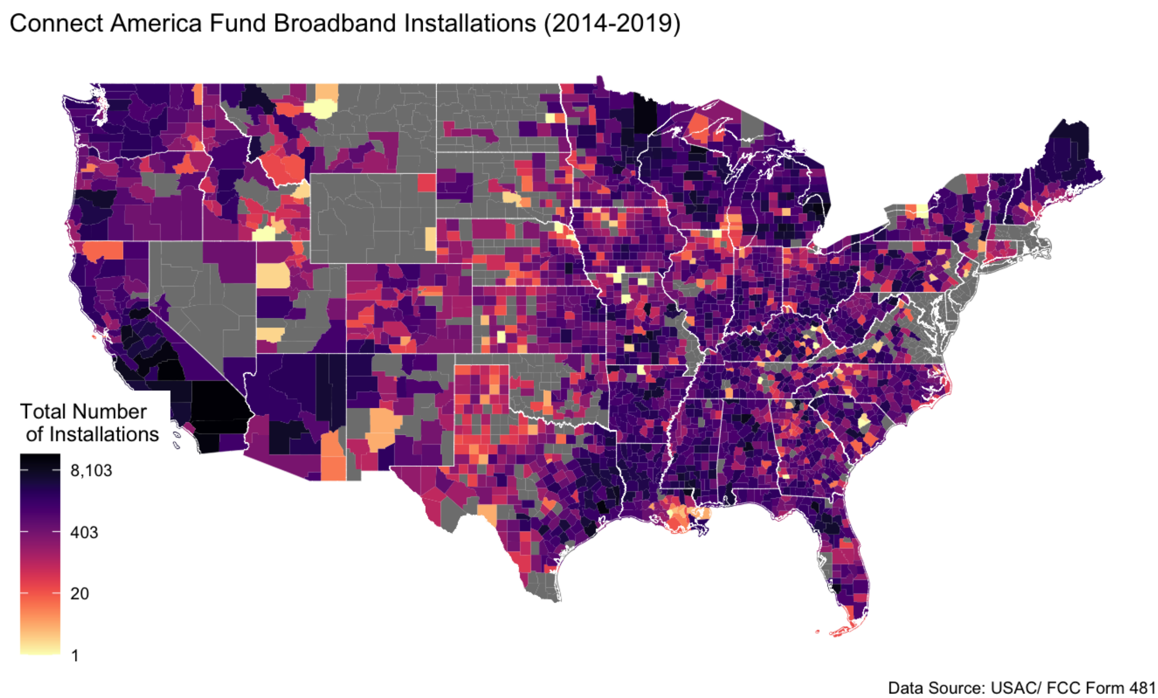
Figure 4 shows that the majority of counties had between 0 and 500 installations with a long tail on the right, where there are up to 6,000 installations.

In Appendix C I show a series of figures describing what predicts installations in a given county. Now that we have established that the program/intervention did result in installations in and financial incentives being provided to telecom providers, the following sections discuss how to estimate the impact of the program on employment outcomes.

6 Empirical Strategy

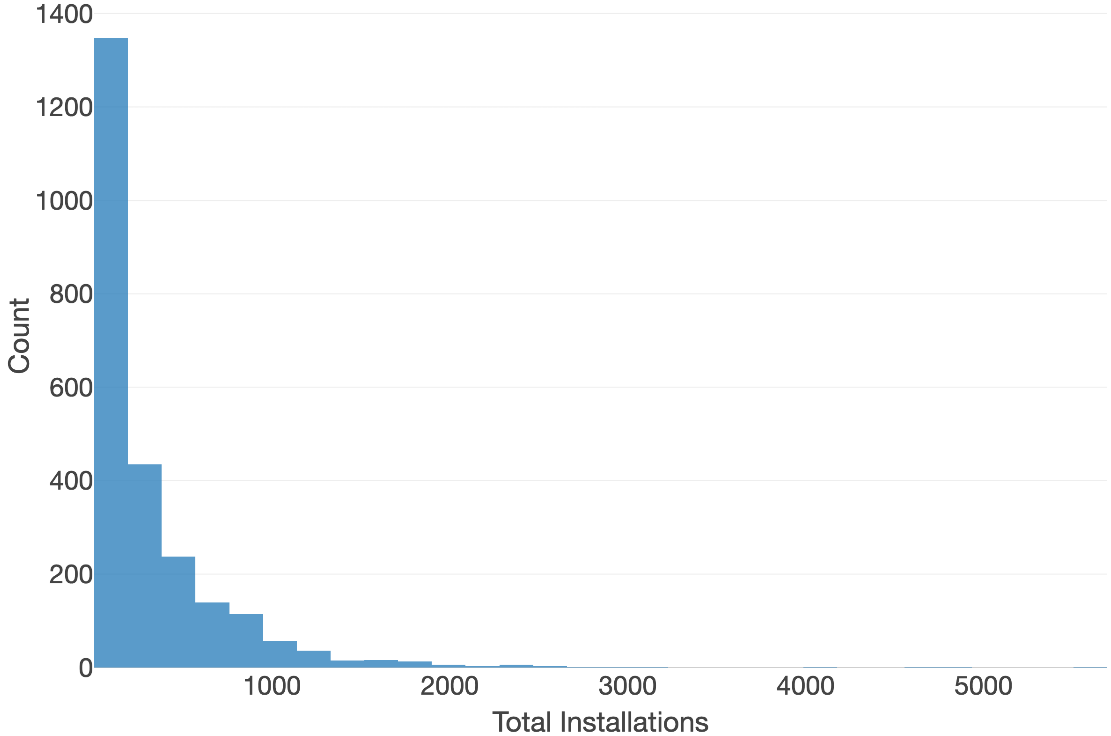
Capturing the impact of broadband internet access on local labor market outcomes poses a unique set of challenges. Technology uptake is correlated with a variety of characteristics counties that may influence other long-run outcomes. Omitted variables due to these factors could dramatically bias the estimated results. To measure the causal impact of broadband access on local labor market measures, I employ a variety of controls along with a matching technique. In this section, I describe the challenges to identification in this setting, followed by my strategy to address these challenges including thee empirical specification for the

Figure 3: Installations by County over the Course of the Program



Note: This figure depicts the total number of broadband installations incentivized in the program from 2014-2019, with the data shaded by county.

Figure 4: Total Installations of Broadband by County (2014-2019)



Note: This figure is a histogram where each tally is a county, to show the distribution of number of installations by county.

regressions.

6.1 Specification

My initial analysis considers three outcomes of interest: average weekly wage growth, employment growth, and establishment growth.

Broadband access is highly correlated to population density and economic development. As Gadiraju et al. (2018) finds, "people who are generally wealthier, employed, and educated tend to have the most access to broadband". This is because internet service providers are highly incentivized by market forces– typically, incumbents make decisions about expansion based on the cost of entering a location as compared to long-term potential profit. It is more expensive to install and deploy broadband technologies in mountainous or heavily forested areas. In urban areas where there is more demand and less cost to wire the market area, there is more access. The setting of this study somewhat adjusts for that, because the reverse auction "equalizes" by subsidizing the cost of entry. Recent program evaluations have shown that this approach was effective for incentivizing ISPs to enter markets that they otherwise would not have. However, there might still be concerns that outside of the cost of entrance, there are other confounding variables we must adjust for in this subset of treated counties in order to measure the impact on productivity and worker outcomes. In an ideal world, I could randomize broadband adoption to counties that in 2014, did not have substantial access and compare wages, employment, and establishment growth in each location. But, complete randomization of local broadband access is not feasible.

I utilize a series of two period difference-in-difference models to examine the impact of annual support on each of my outcomes. I show two sets of regressions for each outcome, with the second set normalizing by the number of census tracts in each county that are eligible for the program (according to a formula developed by the FCC for identifying eligible census blocks).

For each outcome, I estimate two regressions of broadband installations in county l at time 0 (Pre) and time 1 (Post) on the textbflog change of my outcome variables.

$$\log(employment_l) = \beta_0 + \beta_1 log(1 + Annual\_Support_l) + \alpha_t + \delta_l \tag{1}$$

There are two periods, before and after installation.

Annual_Support is a variable calculated by the FCC for allocating funds to service carriers. The FCC's cost model calculated the annual costs per location to provide broadband service to the census blocks in a given area. I sum the allocated funding for all the census blocks in county location l. α_l is the county location l fixed effect term; and λ_t is the time period fixed effect term (there are two periods, before and after the program).

I focus on annual support because, as described in Figure 9, the number of eligible locations in a county for the program is highly correlated with the amount of annual support. This is almost an 'intent-to-treat' variable that measures the. We see that Figure 9 shows there is a much smaller. Note that neither annual support nor total installations are highly correlated with total population. However, Table 4 shows that in a

6.2 Comparing Results by Technological Intensity

In this set of analyses, I look at whether there is heterogeneity in the impact by whether the county has a high level employment in tech intensive sectors. I utilize industry digitization scores from Muro et al. (2017).

Calvino (2018) similarly present a taxonomy of digital intensive sectors, and where high identifies sectors in the top quartile of the distribution of the values underpinning the global taxonomy, medium-high the second highest quartile, medium-low the second lowest, and low the bottom.

Here, *tech_intensive* is a binary variable that is true when the county has high tech intensive employment and is false when it is not. For example, see 11 for the top 20 counties in term of tech intensive employment.

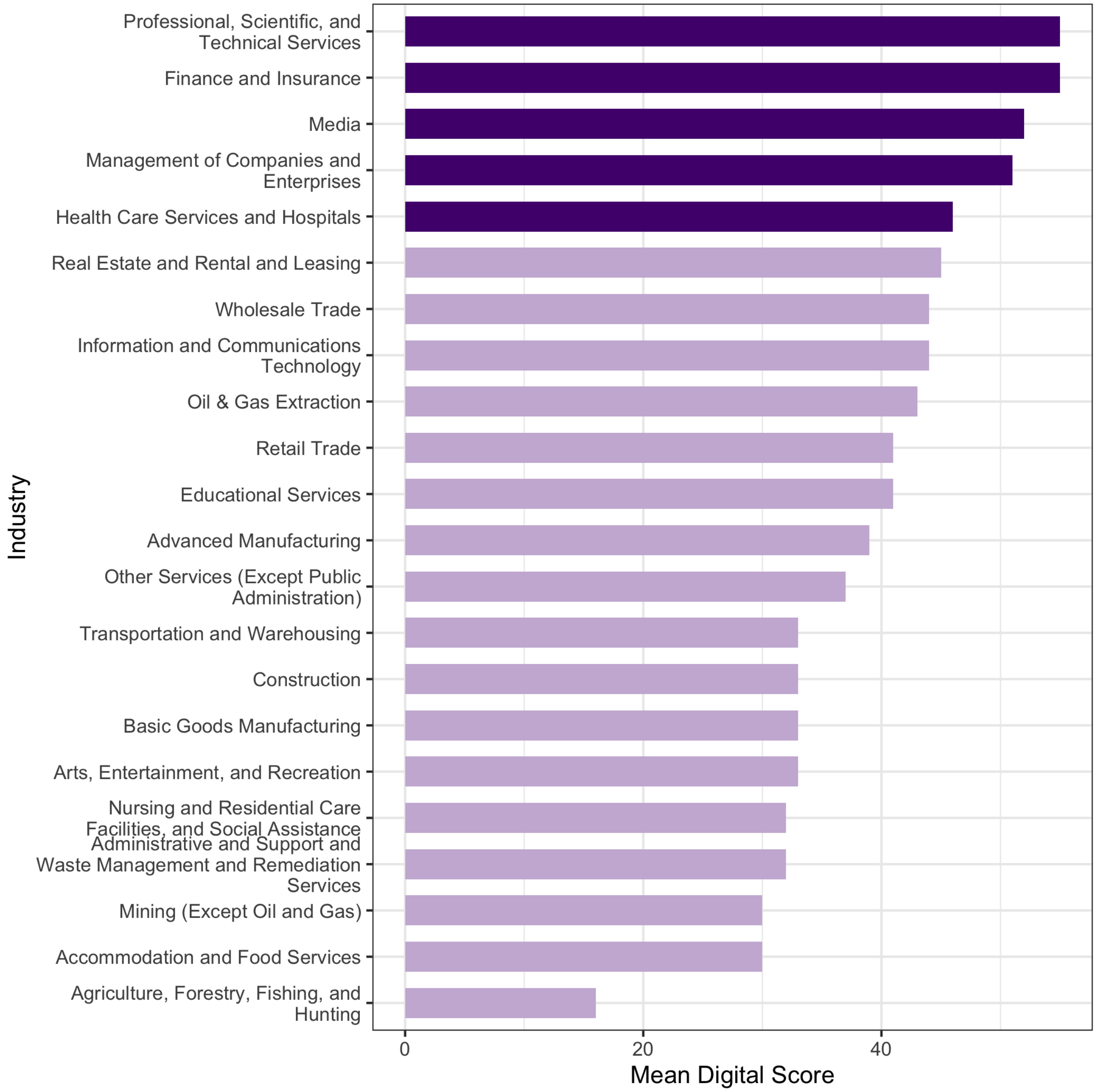
$$\log(employment_l) = \beta_0 + \beta_1 log(1 + Annual\_Support_l) * tech\_intensive_l + \alpha_t + \delta_l \quad (2)$$

Similar to the prior regressions, there are two periods, before and after installation.

7 Program Impact: Difference-In-Differences Model

In this section, I discuss my findings from the regression specifications described in Section 6.

Figure 5: Industry Mean Digitization Scores (2016)



Notes: This figure graphs digitization scores for each NAICS industry (excluding Utilities) based on the analysis in Muro et al. (2017).

7.1 Program support had a positive impact on wages, while impacts on employment level and establishment count are unclear

My base regression, shown in Table 2 shows that there is a positive and significant impact of annual support in a given county on average weekly wages, employment level, and establishments count. On average we see that weekly wages go up in all counties, and employment and establishments trend down. Counties with higher annual support allocated through the program had an increase for all three outcomes.

Table 2: Effect of Program Annual Support on Employment Outcomes

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_annual_support	0.226***	0.707***	0.909***
	(0.067)	(0.114)	(0.099)
Constant	3.436***	−0.333	−5.602***
	(0.927)	(1.577)	(1.367)
Observations	5,773	5,773	5,773
R^2	0.979	0.999	0.999

Notes: Analysis is done at the county level. The independent variable/treatment of interest is annual support. Annual support is the dollar amount allocated by the program to be dispensed annually to subsidize broadband deployment in a given county. Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. This regression is a standard difference-in-differences model with two way fixed effects for county and time period. Time period 1 is 2014, and time period 2 is 2019. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

There are limitations to this regression, because it is possible we are simply seeing that there is an increase in population, which we discuss in the following section.

Additionally, counties' amount of annual support also varies based on the size and population of the county and the number of census blocks that are eligible in the county. We can see from Table1 that the number of eligible tracts in a county varies from 1 to 83 tracts, though the mean is 6.35. One might be concerned that I am not comparing similar counties.

To combat this, in Table 3 I normalize both the amount of annual support and two of the outcomes—employment level and establishment count by the number of eligible tracts. This captures two forms of normalization–population and also program eligibility, since census tracts are divided to have similar population sizes. We see that in Table 3 after normalizing, there is a positive and significant impact on weekly wages, but no positive impact on establishment count or employment level.

Table 3: Effect of Program Annual Support on Employment Outcomes

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_annual_support_norm	1.565***	−1.027	0.370
	(0.463)	(0.788)	(0.683)
Constant	−11.937*	19.569*	0.588
	(5.472)	(9.311)	(8.071)
Observations	5,773	5,773	5,773
R^2	0.979	0.998	0.998

Notes:Analysis is done at the county level. The independent variable/treatment of interest is annual support. Annual support is the dollar amount allocated by the program to be dispensed annually to subsidize broadband deployment in a given county. Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. This regression is a standard difference-in-differences model with two way fixed effects for county and time period. Time period 1 is 2014, and time period 2 is 2019. Table is similar to eftab:baseregression but in this table, I normalize the treatment variable, employment level, and establishment count. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : * * *$.

7.2 Program Support has a positive impact on population

In Table 4, I use a two-way fixed effects regression and show that both annual support and total installation. have a positive when regressed on population in a given period. More details on total installations as a treatment variable is discussed in Appendix C.

Table 4: Annual Support and Installations on Population

	Dependent variable:			
	Population			
	(1)	(2)	(3)	(4)
log1p_installations	0.200***			
	(0.005)			
log1p_installations_norm		0.237***		
		(0.006)		
log1p_annual_support			0.152***	
			(0.003)	
log1p_annual_support_norm				0.175***
				(0.003)
Constant	9.278***	9.402***	8.856***	8.856***
	(0.030)	(0.028)	(0.026)	(0.026)
Observations	4,896	4,896	5,696	5,696
R^2	1.000	1.000	1.000	1.000

Notes: This table shows a county-level regression with population as the outcome variable. The table depicts the result of regressing annual support (Column 1) on population, regressing annual support normalized (Column 2) by the number of eligible tracts, regressing total installations (Column 3) on population , regressing total installations normalized (Column 4) by the number of eligible tracts on population to see whether program eligibility and broadband access through the program is correlated with an increase in population. This includes a fixed effect for period and for county id. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

7.3 Program Support is particularly beneficial for less tech-intensive counties

I find that program Support is particularly beneficial for counties with less technology intensive employment before the program.

Table 5 shows the results of a triple interaction framework where *tech_intensive*_75 is interacted with $log1 + annual\_support$ and the time period.

I find that counties that are tech intensive have positive growth in weekly wages, employment level, and establishments over time. However, tech intensive counties have less positive benefit from getting annual support, than the non-tech intensive industries.

Results are similar with and without normalization. A version of Table 5 without normalization of the treatment and population-related outcome variables is in Appendix D. I check for robustness to shifting the threshold for the $tech\_intensive$ dummy variable to the top 10th percentile rather than top 25th percentile and find similar results in Table 10.

Table 5: Effect of of Program Annual Support $ on Employment Outcomes (Tech Intensity)

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_annual_support_norm	-0.007^{***}	-0.101^{***}	-0.106^{***}
	(0.002)	(0.010)	(0.009)
tech_intensive_75	0.436^{***}	3.985^{***}	3.614^{***}
	(0.042)	(0.214)	(0.190)
log1p_annual_support_norm:tech_intensive_75	-0.028^{***}	-0.254^{***}	-0.234^{***}
	(0.004)	(0.020)	(0.018)
Constant	6.600^{***}	8.474^{***}	6.027^{***}
	(0.022)	(0.111)	(0.098)
Observations	5,608	5,608	5,608
R^2	0.248	0.428	0.441

Notes: This table depicts a triple interaction regression at the county level, with annual support, a dummy variable for whether the county has higher than the 25th percentile in terms of employent in tech intensive industries according to BEA data and digitization scores from Muro (2017). I normalize the treatment variable, employment level, and establishment count. Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages.Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

8 Discussion & Conclusion

In this paper, I explored the relationship between broadband and local labor market outcomes in areas that are were underserved in terms of broadband access prior to a federal program.

The prior literature on broadband has found that broadband has positive impacts on employment and wages, particular for regions and individuals that are higher skilled and more tech-intensive prior to expanded broadband access.

In the areas where this program was rolled, these areas were disproportionately rural, with lower skilled workers. So, we might expect to not find positive benefits from these programs due to a lack of complementary skills and resources. To examine whether this is the case, I combine descriptive results with causal identification of program impact on local employment outcomes.

Retrospective program evaluation provides valuable insights into the effectiveness of a program. It can pinpoint what worked and what didn't work, allowing program designers to adjust and improve the program going forward. It also helps to identify areas of opportunities to be explored that could lead to effective and efficient program implementation. By reviewing past programs, organizations can use the knowledge gained to inform new projects and initiatives, increasing the overall success rate for those programs. Economics of information systems researchers are well-positioned to combine theory with causal program evaluation and consider the potential unintended consequences.

I find that program support had a positive impact on wages, while impacts on employment level and establishment count are unclear, given that there was an overall positive impact of the program on population. I also find that program Support is particularly beneficial for less tech-intensive counties.

This result aligns with prior work that finds that broadband access reduces/mitigates depopulation in rural areas (Briglauer et al., 2019). However, it contradicts prior work that finds that broadband access is particularly beneficial for higher skilled individuals in tech intensive employment environment (Akerman et al., 2015; Kolko, 2010).

It is likely this is because of the design of the program explicitly incentivized telecom companies to enter the most disadvantaged markets by offsetting the high expense and lower profit potential. Prior work often looked at broadband deployment as a natural experiment that rolled out, but broadband access was often endogenous to the factors that were used in this federal program to calculate the size of the subsidy (i.e. geographic attributes, economic development, and amount of existing infrastructure).

Further work should explore in more detail what factors predict a positive benefit from the program. This result reinforces the fact that in the context of broadband interventions in rural local environments, a consideration of, nuanced view of the determinants whether communities reap the benefits of broadband technology is crucial. Further work in this area will allow the government to design policies that complement the technology and allows for broad benefits. In particular, designing market mechanisms to counteract the digital divide can provide both data on the impact of technology.

Bibliography

Acemoglu, Daron and Pascual Restrepo, "Modeling Automation," 2018.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad, "The Skill Complementarity of Broadband Internet," *The Quarterly Journal of Economics*, 11 2015, *130* (4), 1781–1824.

Almeida, Rita, Corseuil Carlos H. L, and Jennifer Poole, "The Impact of Digital Technologies on Worker Tasks: Do Labor Policies Matter?," *IZA Discussion Papers*, 2017, (December).

Alper, Emre and Michal Miktus, "Digital Connectivity in sub-Saharan Africa," *IMF Working Papers*, 2019, *19* (210).

Atasoy, Hilal, "The Effects of Broadband Internet Expansion on Labor Market Outcomes," *ILR Review*, 4 2013, *66* (2), 315–345.

Autor, David, David Dorn, and Gordon Hanson, "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men," *American Economic Review: Insights*, 9 2019, *1* (2), 161–178.

Autor, David H, F Levy, and R J Murnane, "Skill demand, inequality, and computerization: Connecting the dots," *Technology, Growth, and the Labor Market*, 2003, (December), 107–129.

_ , Lawrence F Katz, and Melissa S Kearney, "The Polarization of the U.S. Labor Market," in "NBER Working Paper Series" number 11986 2006.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge, "What Happens to Workers at Firms that Automate?," 2020.

Bhuller, Manudeep, Andreas R Kostøl, and Trond C Vigtel, "How Broadband Internet Affects Labor Market Matching," 2019.

Black, Sandra E and Alexandra Spitz-Oener, "Explaining Women's Success: Technological Change and the Skill Content of Women's Work," *Review of Economics and Statistics*, 2010.

Bresnahan, Timothy F. and M. Trajtenberg, "General purpose technologies 'Engines of growth'?," *Journal of Econometrics*, 1995, *65* (1), 83–108.

Briglauer, Wolfgang and Klaus Gugler, "Go for Gigabit? First Evidence on Economic Benefits of High-speed Broadband Technologies in Europe," *Journal of Common Market Studies*, 2019, *57* (5), 1071–1090.

_, Niklas S. Dürr, Oliver Falck, and Kai Hüschelrath, "Does state aid for broadband deployment in rural areas close the digital and economic divide?," *Information Economics and Policy*, 2019, *46* (16), 68–85.

Calvino, Flavio, "A taxonomy of digital intensive sectors," 2018.

Cariolle, Joël, "Telecommunication submarine-cable deployment and the digital divide in sub-Saharan Africa," 2018, pp. 1–39.

_, Maëlan Le Goff, and Olivier Santoni, "Digital Vulnerability and Performance of Firms in Developing Countries," Technical Report 2018.

DeStefano, Timothy, Richard Kneller, and Jonathan Timmis, "Broadband infrastructure, ICT use and firm performance: Evidence for UK firms," *Journal of Economic Behavior and Organization*, 2018, *155*, 110–139.

Dettling, Lisa J, "Broadband in the Labor Market: The impact of residential high-speed internet on Married Women's Labor Force Participation," *ILR Review*, 2017, *70* (2), 451–482.

_, Sarena Goodman, and Jonathan Smith, "Every Little Bit Counts: The Impact of High Speed Internet on the Transition to College," *Review of Economics and Statistics*, 2018, *100* (2), 260–273.

Forman, Chris, Avi Goldfarb, and Shane Greenstein, "The Internet and Local Wages: A Puzzle," *American Economic Review*, 2012, *102* (1), 556–575.

Gadiraju, Vamsi, Anthony Panat, Raghav Poddar, Zain Sherriff, Sam Kececi, and Henning Schulzrinne, "Who Gets Broadband When? A Panel Data Analysis of Demographic, Economic and Technological Factors Explaining U.S. Broadband Deployment," *SSRN Electronic Journal*, 2018.

Gilbert, Melissa, "Theorizing digital and urban inequalities: Critical geographies of 'race', gender and technological capital," *Information Communication and Society*, 2010, *13* (7), 1000–1018.

Glass, Victor and Timothy Tardiff, "The Federal Communications Commission's rural infrastructure auction: What is hidden in the weeds?," *Telecommunications Policy*, 2019, *43* (8), 101821.

Gonzales, Amy, "The contemporary US digital divide: from initial access to technology maintenance," *Information Communication and Society*, 2016, *19* (2), 234–248.

Greenstein, Shane and Ryan C. McDevitt, "The Broadband Bonus: Accounting for Broadband Internet's Impact on U.S. GDP," 2009.

Grubesic, Tony H., "The spatial distribution of broadband providers in the United States: 19992004," *Telecommunication Policy*, 2008, *32*, 212–233.

Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya, "3G Internet and Confidence in Government," Technical Report 2020.

Holt, Lynne and Mark Jamison, "Broadband and contributions to economic growth: Lessons from the US experience," *Telecommunications Policy*, 2009.

Katz, Raul, "The Impact of Broadband on the Economy: Research to Date and Policy Issues," Technical Report 2012.

Katz, Raul L., Fernando Martin Callorda, and Juan Jung, "Can Digitization Mitigate COVID-19 Damages? Evidence from Developing Countries," *SSRN Electronic Journal*, 2020, pp. 1–25.

Kolko, Jed, "A new measure of US residential broadband availability," *Telecommunications Policy*, 2010, *34* (3), 132–143.

Mack, Elizabeth A., William H. Dutton, R. V. Rikard, and Aleksandr Yankelevich, "Mapping and measuring the information society: A social science perspective on the opportunities, problems, and prospects of broadband Internet data in the United States," *Information Society*, 2019, *35* (2), 57–68.

Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni, "Digitalization and the American Workforce," Technical Report November, Brookings Institution, Washington, D.C. 2017.

Oh, Sarah, "What Are the Economic Effects of Municipal Broadband?," Technical Report, Technology Policy Institute, Washington, D.C. 2019.

Poliquin, Christopher W, "The Wage and Inequality Impacts of Broadband Internet," 2020.

Rohman, Ibrahim Kholilul and Erik Bohlin, "Does Broadband Speed Really Matter for Driving Economic Growth? Investigating OECD Countries," *SSRN Electronic Journal*, 2012, pp. 1–16.

Stenberg, Peter, Mitch Morehart, Stephen Vogel, John Cromartie, Vince Breneman, and Dennis Brown, "Broadband internets value for rural America," *Rural America: Issues and Developments*, 2010, (78), 59–114.

Suhaida, M. A., M. S. Nurulhuda, and Su-Fei Yap, "Access to ICT as Moderating Factor to Womens Participation in the Labor Force: A Conceptual Framework," *International Journal of Trade, Economics and Finance*, 8 2013, *4* (4), 197–201.

Tomer, Adie, Elizabeth Kneebone, and Ranjitha Shivaram, "Signs of Digital Distress," Technical Report, Brookings Institute, Washington, D.C. 9 2017.

Whitacre, Brian and Roberto Gallardo, "State broadband policy: Impacts on availability," *Telecommunications Policy*, 2020, *44* (9), 102025.

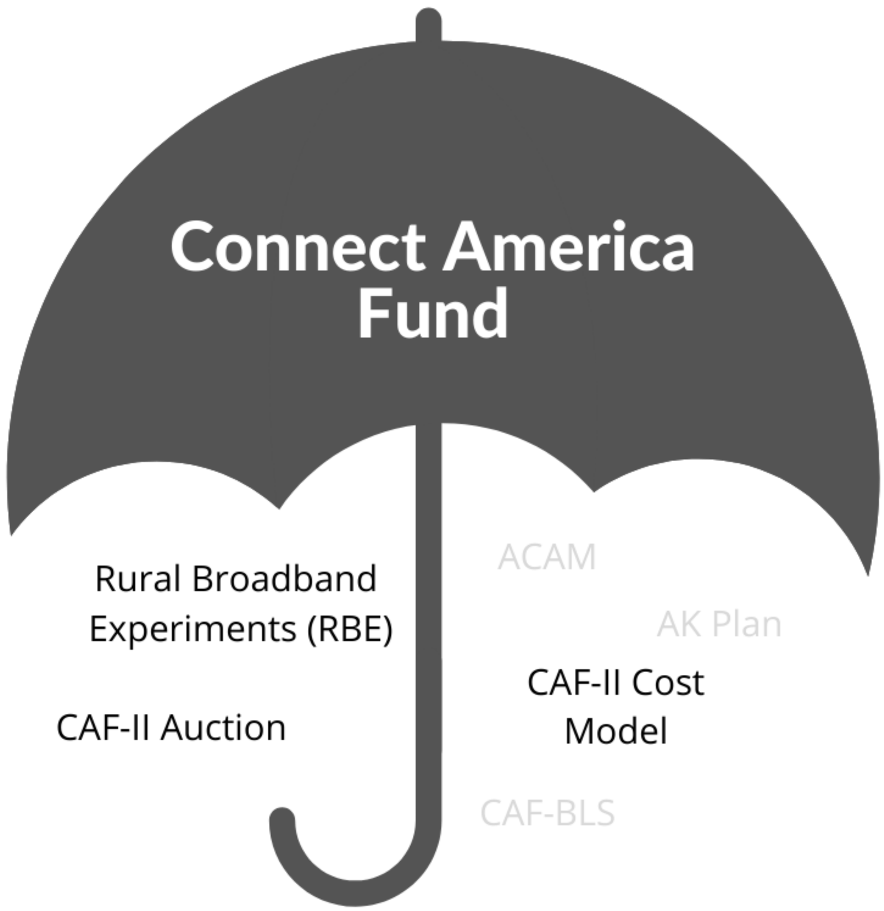
_ , _ , and Sharon Strover, "Does rural broadband impact jobs and income? Evidence from spatial and first-differenced regressions," *Annals of Regional Science*, 2014, *53* (3), 649–670.

Appendices

A Connect America Fund Program Details

The federal program examined in this is essentially a set of programs with a common goal, but different mechanisms and eligibility criteria. Figure 6 lists all of the programs that are contained within the program.

Figure 6: Visualization of Connect America Fund Program

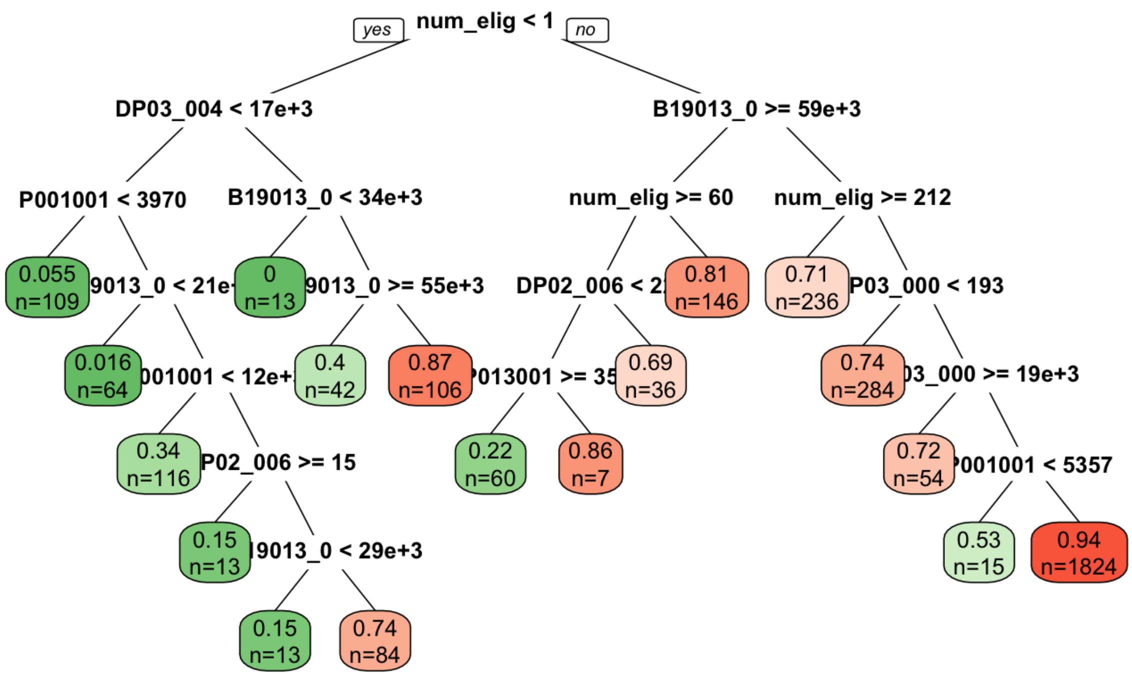


Note: This image depicts the Connect America Fund program, which is a collection of programs/initiatives to bring broadband internet throughout the U.S.. In bold are the programs I focus on in this paper.

The key program discussed in this paper is the FCC's CAF-II auction. The FCC's CAF-II auction is a reverse auction administered by the Federal Communications Commission (FCC) to award funding to companies that provide broadband services in rural and underserved areas. The auction is designed to award the highest support amounts to those bids that meet certain criteria while spending the least amount of money. Bidders must demonstrate their ability to build and maintain a broadband service subscription in the area they are providing service to in order to qualify for the auction. The auction utilizes a descending clock format (a form of reverse, private-value auction where the auction price ticks down. The auction ends when a bidder first claims the good and accepts the current price.) and requires bidders to submit package bids for a collection of census blocks. The 'winner' of the auction receives funding for the set of geographic areas they bid on.

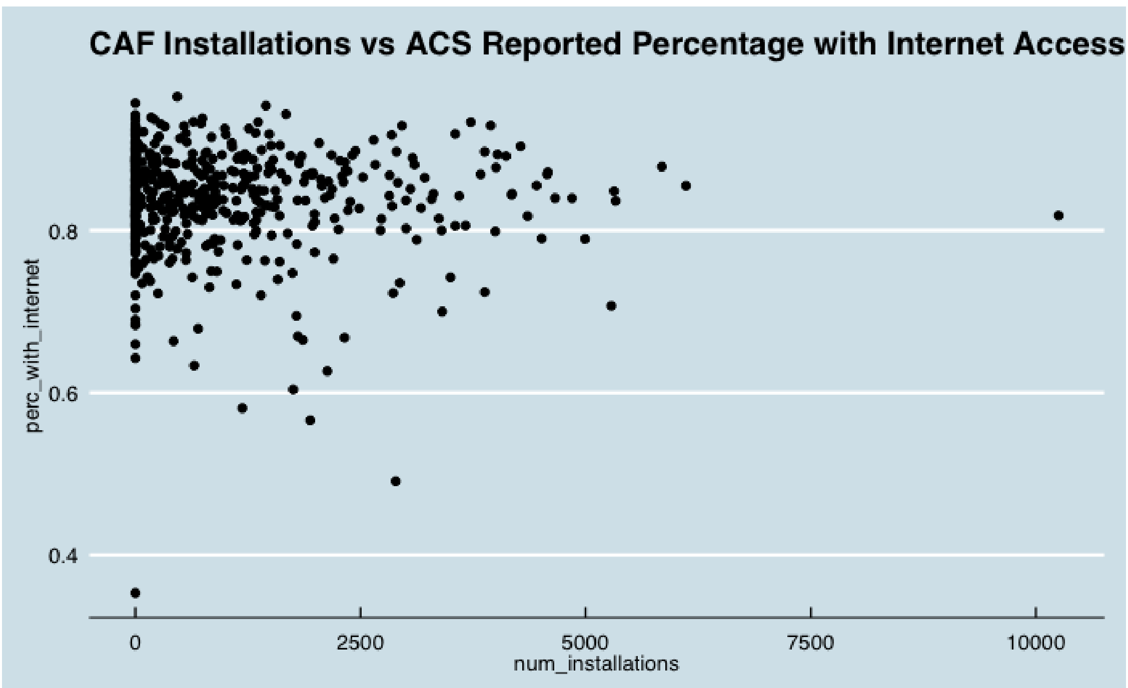
B What predicts the number of broadband installations?

Figure 7: Decision Tree that predicts whether a given county has eligible blocks



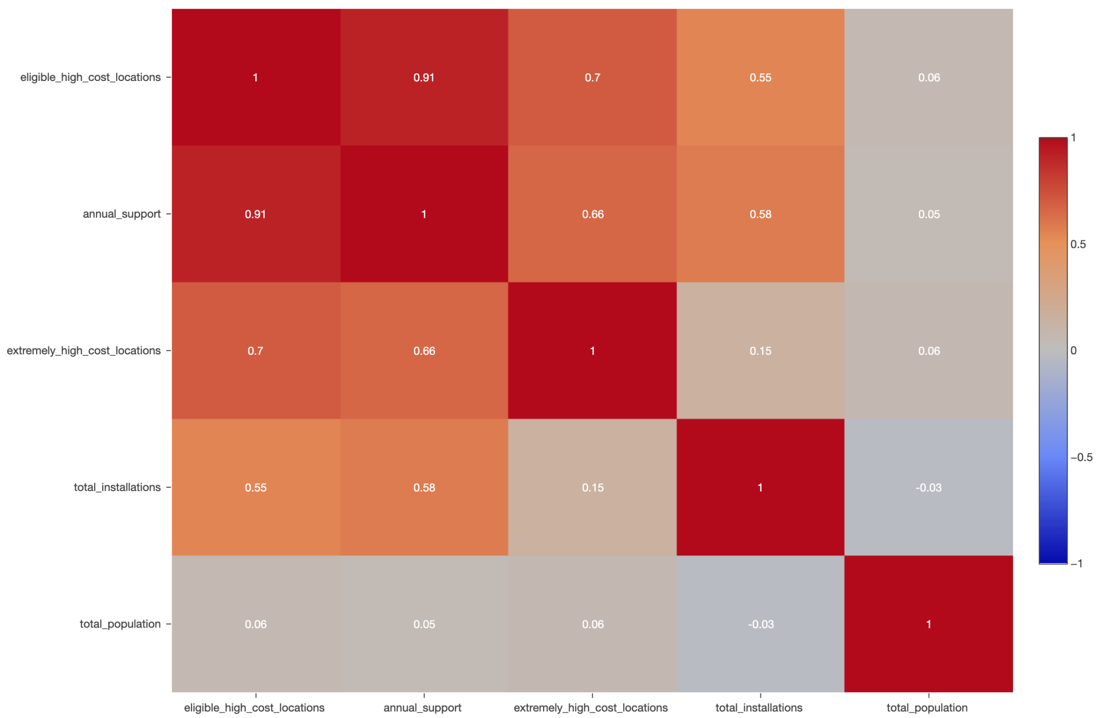
Notes: This figure depicts a decision tree calculated via rpart (logistic regression tree) that predicts whether a given county will have any eligible blocks, based on American Community Survey data about the county

Figure 8: Correlation between installations and percentage with internet access



Notes: This figure depicts the correlation between internet access according to American Community Survey data in 2010, and the number of installations a county had via the CAF-II programs

Figure 9: Correlation between installations and percentage with internet access



Notes: This figure depicts the correlations between program impact variables at the county level: including the number of eligible high cost locations, the amount of annual support allocated by the program, the number of extremely high cost locations, the total number of installations through the program, and the total population.

C Alternative Specification: Treatment as Total Installations

The specification here is almost identical to that described in Subsection 6.1, but here we consider the impact of the actual installations, rather than the annual support promised by the governmental program. My analysis considers three outcomes of interest: average weekly wage growth, employment growth, and establishment growth.

Total Installations is a variable that measures the number of locations (houses or businesses) that received access to broadband under the program in a county.

For each outcome, I estimate two regressions of broadband installations in county l at time 0 (Pre) and time 1 (Post) on the textbflog change of my outcome variables.

$$\log(employment_l) = \beta_0 + \beta_1 log(1 + Total\_Installations_l) + \alpha_t + \delta_l \tag{3}$$

There are two periods, before and after installation. $Total\_Installations$ is the number of installations under the program during the program in a given county (location l). α_l is the county location l fixed effect term; and λ_t is the time period fixed effect term (there are two periods, before and after the program).

It's likely that our result here is driven by the increase in population from period 1 to period 2.

Findings

Table 6: Effect of Installations on Employment Outcomes

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_installations	0.002	0.128^{***}	0.088^{***}
	(0.006)	(0.010)	(0.009)
Constant	6.489^{***}	8.216^{***}	6.012^{***}
	(0.036)	(0.060)	(0.053)
Observations	4,896	4,896	4,896
R^2	0.975	0.999	0.999

Notes: Analysis is done at the county level. The independent variable/treatment of interest is total number of installations. Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are all sourced from the Quarterly Census of Employment and Wages and this regression is a standard difference-in-differences model with two way fixed effects for county and time period. Time period 1 is 2014, and time period 2 is 2019. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

Table 7: Effect of Program Total Installations on Employment Outcomes

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_installations_norm	0.003	0.084***	0.037***
	(0.007)	(0.012)	(0.011)
Constant	6.490***	6.936***	4.708***
	(0.033)	(0.055)	(0.049)
Observations	4,896	4,896	4,896
R^2	0.975	0.998	0.998

Notes:Analysis is done at the county level. The independent variable/treatment of interest is total number of installations. Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. This regression is a standard difference-in-differences model with two way fixed effects for county and time period. Time period 1 is 2014, and time period 2 is 2019. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

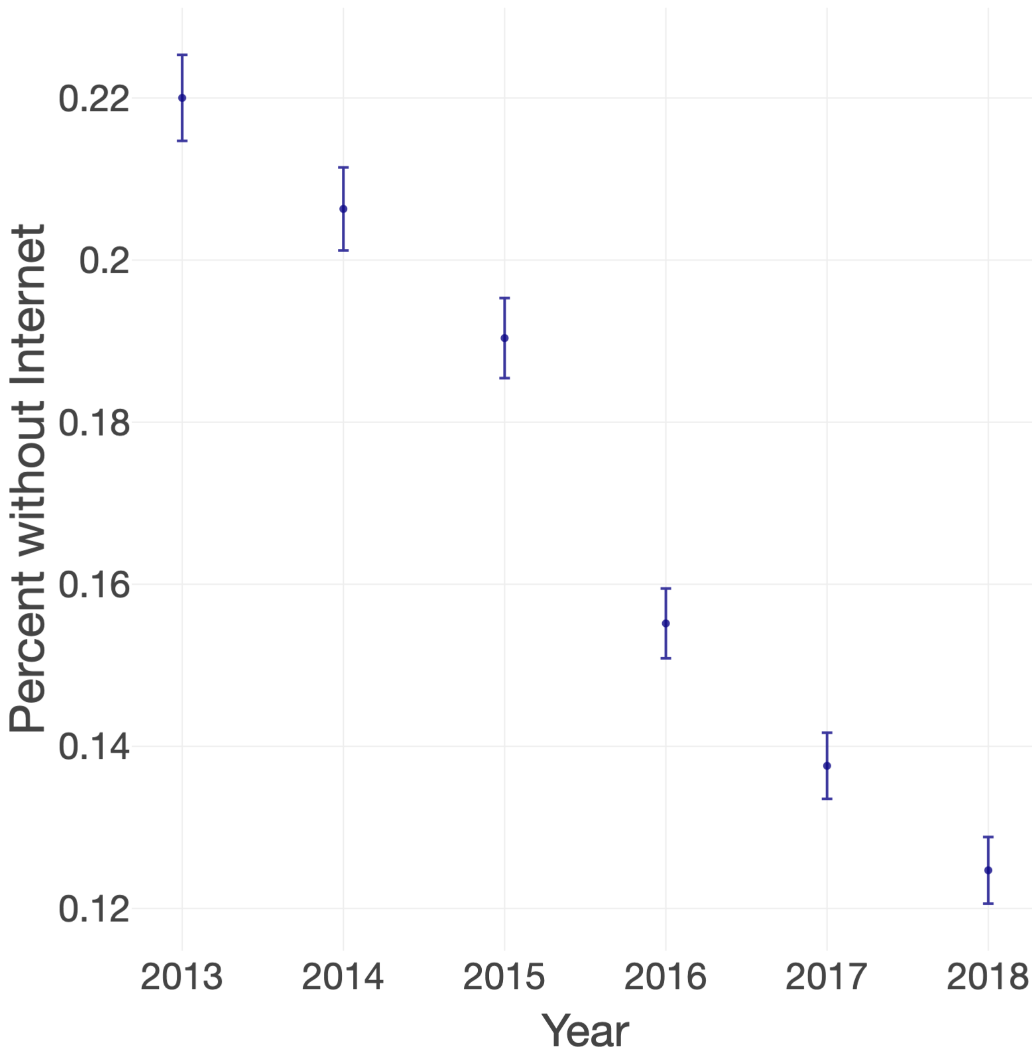
Table 8: Effect of Installations on Employment Outcomes (Tech Intensity)

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_installations	-0.003	0.160^{***}	0.122^{***}
	(0.002)	(0.016)	(0.014)
tech_intensive_75	0.217^{***}	3.252^{***}	2.786^{***}
	(0.031)	(0.209)	(0.182)
log1p_installations:tech_intensive_75	-0.010^{*}	-0.184^{***}	-0.136^{***}
	(0.005)	(0.032)	(0.028)
Constant	6.530^{***}	7.703^{***}	5.438^{***}
	(0.016)	(0.108)	(0.094)
Observations	4,872	4,872	4,872
R^2	0.236	0.402	0.426

Notes: This table depicts a triple interaction regression at the county level, with number of installations, a dummy variable for whether the county has higher than the 25th percentile in terms of employent in tech intensive industries according to BEA data and digitization scores from Muro (2017). Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

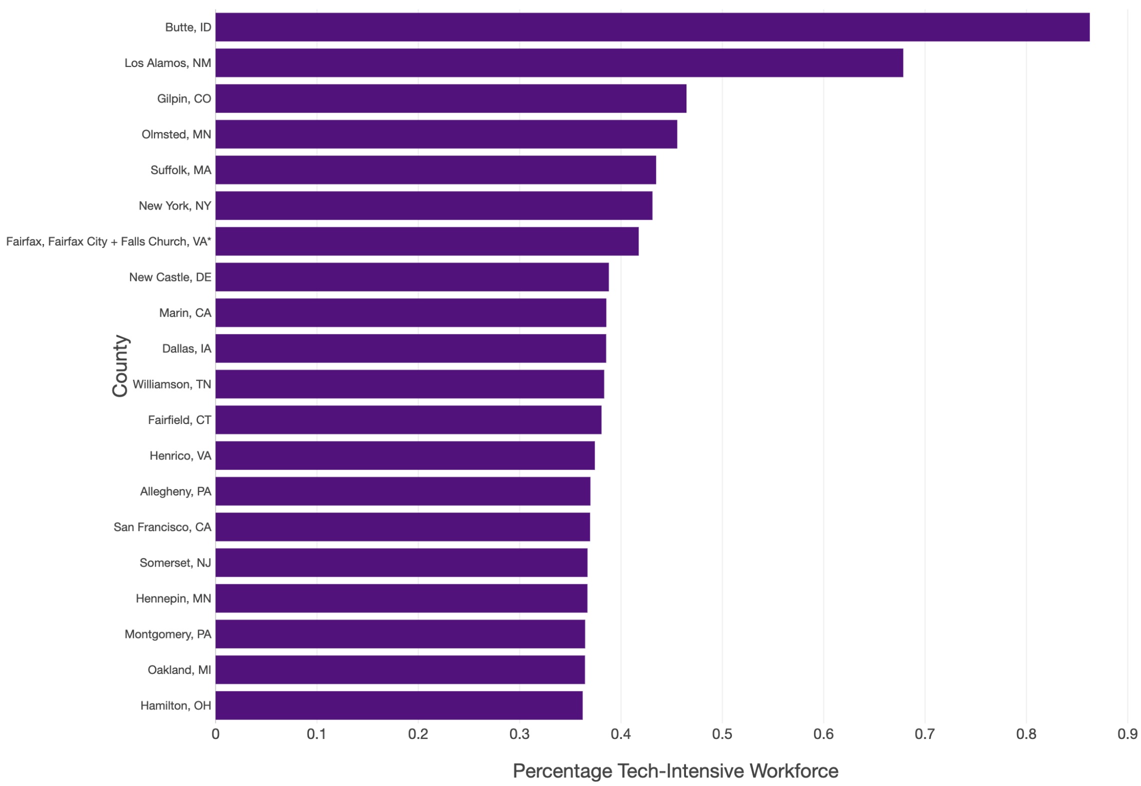
D Additional Tables & Figures

Figure 10: Average Percentage of Households without Internet Access in County



Notes: This figure depicts the percentage of households without internet access over time (2013-2018), according to available data from the American Community Survey.

Figure 11: Top 20 Counties by Employment in Tech-Intensive Industries



Notes: This figure depicts the top 20 counties by tech intensive employment based on industry digitization scores in (Muro et al., 2017) and industry employment by county data from the BEA.

Table 9: Effect of of Program Annual Support $ on Employment Outcomes (Tech Intensity)

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_annual_support	$-0.003^{\dagger}$	0.100^{***}	0.079^{***}
	(0.002)	(0.011)	(0.010)
tech_intensive_75	0.372^{***}	4.771^{***}	4.332^{***}
	(0.042)	(0.277)	(0.241)
log1p_annual_support:tech_intensive_75	-0.018^{***}	-0.210^{***}	-0.188^{***}
	(0.003)	(0.023)	(0.020)
Constant	6.556^{***}	7.425^{***}	5.192^{***}
	(0.021)	(0.139)	(0.121)
Observations	5,608	5,608	5,608
R^2	0.231	0.422	0.449

Notes: This table depicts a triple interaction regression at the county level, with annual support, a dummy variable for whether the county has higher than the 25th percentile in terms of employent in tech intensive industries according to BEA data and digitization scores from Muro (2017). Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : * * *$.

Table 10: Effect of of Program Annual Support $ on Employment Outcomes (Tech Intensity)

	Dependent variable:		
	Log(Weekly Wage)	Log(Employment)	Log(Establishment Count)
	(1)	(2)	(3)
log1p_annual_support_norm	-0.011^{***}	-0.152^{***}	-0.150^{***}
	(0.002)	(0.009)	(0.008)
tech_intensive_90	0.654^{***}	4.557^{***}	4.241^{***}
	(0.062)	(0.337)	(0.296)
log1p_annual_support_norm:tech_intensive_90	-0.043^{***}	-0.280^{***}	-0.266^{***}
	(0.006)	(0.034)	(0.030)
Constant	6.653^{***}	9.204^{***}	6.662^{***}
	(0.019)	(0.103)	(0.091)
Observations	5,608	5,608	5,608
R^2	0.272	0.376	0.402

Notes: This table depicts a triple interaction regression at the county level, with annual support, a dummy variable for whether the county has higher than the 25th percentile in terms of employent in tech intensive industries according to BEA data and digitization scores from Muro (2017). Weekly wage (Column 1), employment level (Column 2), and establishment count (Column 3) are the outcomes of interest—all three are sourced from the Quarterly Census of Employment and Wages. I normalize the treatment variable, employment level, and establishment count. Significance: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.