Telecommunications Policy 46 (2022) 102310

Contents lists available at ScienceDirect

Telecommunications Policy

journal homepage: www.elsevier.com/locate/telpol

Broadband adoption and availability: Impacts on rural employment during COVID-19

Catherine Isley *, Sarah A. Low

Division of Applied Social Sciences, College of Agriculture, Food and Natural Resources, University of Missouri, USA

A R T I C L E I N F O

Keywords:
Broadband
COVID-19 pandemic
Employment
Rural economic development
Broadband adoption
Broadband availability

A B S T R A C T

Amidst COVID-19-related stay-at-home orders, the economy moved largely online and broadband internet became more important than ever. This paper explores the relationship between broadband and employment rates during April and May 2020 in rural U.S. counties. We use two broadband dimensions: infrastructure availability rates and household adoption rates. We use a two-stage least squares approach to address endogeneity and control for socioeconomic, demographic, and pandemic-related factors. Results show broadband availability and wired broadband adoption both had significant, positive impacts on the employment rate. Our findings suggest both broadband adoption and availability may be associated with economic benefits in rural America.

1. Introduction

Over the past two decades, a so-called "digital divide" between high-speed broadband internet in rural and urban areas has emerged. Illustratively, in 2018, 98.5% of urban residents had broadband access, while only 77.7% of rural residents did (Federal Communications Commission, 2020). This digital divide is problematic because broadband has been shown to have a multitude of economic benefits, including higher employment, higher median household incomes, increased numbers of firms and establishments, and increased entrepreneurial activity (Kolko, 2012; Conroy & Low, 2022; Mack, Anselin, and Grubesic, 2011; Whitacre, Gallardo, and Strover, 2014a). Therefore, rural areas – already disadvantaged economically – may be missing out on these benefits.

It is likely that the economic benefits attributable to broadband were large during the COVID-19 pandemic. Social distancing, induced by the pandemic, led the economy to rely on e-commerce and remote work more than ever before, as was found during the SARS pandemic (Katz, Jung and Callordo, 2020). In May 2020, 35.2% of the U.S. workforce was working remotely full time, compared to 8.2% in February of 2020 (Bick, Blandin, and Mertens, 2020). Additionally, 16.1% of retail sales were conducted online in the second quarter of 2020, up from the pre-pandemic rate of 11.3% (United States Census Bureau, 2021). This equates to over a 40% spike in e-commerce, the largest in U.S. history. Clearly, the pandemic placed rural areas without broadband at a disadvantage when it came to work and commerce.

Understanding how broadband affected rural employment during the COVID-19 pandemic may be useful in helping us understand how broadband will impact rural areas in an era of increasing technological reliance. That is, the findings shared in this paper are not just useful in the context of future pandemics and disasters. Even before the pandemic began, our reliance on technology had been increasing. For example, from 2000 to 2019, e-commerce as a percentage of retail sales saw a compound annual growth rate of near

* Corresponding author.
E-mail addresses: catherine.isley@mail.missouri.edu (C. Isley), lowsa@missouri.edu (S.A. Low).

https://doi.org/10.1016/j.telpol.2022.102310
Received 6 August 2021; Received in revised form 21 January 2022; Accepted 22 January 2022
Available online 3 February 2022
0308-5961/

18% (United States Census Bureau, 2021). And from 2010 to February 2020, the proportion of Americans working at least part-time from home rose nearly 14 percentage points (Bick et al., 2020). We are seeing some decrease in reliance on digital connectivity post-pandemic, as many activities shift back to face-to-face, but assuming this pre-pandemic trend of tech reliance resumes, over time our degree of technological reliance may again reach levels experienced during the pandemic. Therefore, it's important to understand how broadband has impacted rural economies amidst the pandemic, as this impact may be indicative of broadband's future economic benefits and consumers' future broadband needs.

Specifically, in this paper we explore the relationship between broadband penetration and the employment rate in rural counties during the height of COVID-19-related disruptions. We examine three measures of penetration: broadband availability, wired broadband adoption, and any internet adoption. Two-stage least squares is the primary estimator used. Our two-stage least squares estimations utilize a set of terrain-related instrumental variables.

Results show that during the height of pandemic-related disruptions, *broadband availability* and *wired broadband adoption* both had statistically significant, causal relationships with the employment rate in low-population rural counties. Specifically, a one percentage point increase in the rate of broadband availability would have led to a 0.37 percentage point increase in the employment rate ($p < 0.001$). A one percentage point increase in the rate of wired broadband adoption would have led to a 0.87 percentage point increase in the employment rate ($p < 0.001$). Results for *any internet adoption* are inconclusive. Results surrounding wired adoption are largely in line with the literature. Availability results are consistent with studies showing positive impacts in the early days of broadband (Conroy & Low, 2022; Kolko, 2012; Lehr, Osorio, Gillett, & Sirbu, 2006) but run counter to recent studies finding that broadband availability has little relationship with economic benefits (Gallardo, Whitacre, Kumar, & Upendram, 2021; Whitacre et al., 2014a; Whitacre, Gallardo, and Strover, 2014b).

This paper makes several contributions to the existing literature. First, the two-stage least squares estimator allows us to draw causal conclusions, unlike estimators used in much of the literature. Additionally, somewhat novel instruments for broadband are used. The measures we use for broadband adoption are also somewhat novel, as literature to-date utilizes the measure "broadband access" (paid or unpaid broadband adoption, whether at home or in public), while we use measures of paid household subscriptions to specific broadband technologies (i.e., fiber, cable and DSL). Lastly, conducting the analysis on the peak of COVID-19 disruptions allows us to explore the impact of broadband in a time when individuals had been relying on broadband for work and commerce more than ever before.

The paper commences by exploring literature surrounding employment and broadband use during the pandemic, broadband's economic benefits, and adoption versus availability. We then discuss our data and choice of estimator, two-stage least squares, using percent of county that is forested and percent of county that is wetland as our instrumental variables. Finally, we discuss results, provide policy implications, and conclude.

2. Literature review

2.1. Trends in employment and broadband during the COVID-19 pandemic

The COVID-19 pandemic impacted the U.S. labor market. Pre-pandemic, in February 2020, the unemployment rate was 3.5% (Bureau of Labor Statistics, 2020a). In April 2020 the unemployment rate peaked at 14.7%, the highest rate in the seven decades since data collection began (Bureau of Labor Statistics, 2020b). Labor force participation was also impacted. The labor force participation rate was 63.4% as of February 2020 and, as fears about the virus peaked, dropped to a low of 60.2% in April 2020, a level not seen in five decades (Bureau of Labor Statistics, 2020a; Bureau of Labor Statistics, 2020b).

At the peak of COVID-19-related disruptions, labor market impacts varied across economic sectors and demographic groups. The *Leisure and Hospitality Sector* was the most badly hit, with a sector-wide unemployment rate of 39.3% in April 2020 (Congressional Research Service, 2021b). *Other Services* and *Wholesale and Retail Trade* were also strongly affected (Congressional Research Service, 2021b). Judging by the unemployment rate, *Financial Activities* (5.7%), *Government* (9.3%), and *Professional and Business Services* (9.8%) were among the least impacted sectors, though job losses paint a different picture, with *Government* losing one of the largest shares of jobs (Congressional Research Service, 2021b). Pandemic-era labor market conditions also varied by demographic group. Black and Hispanic individuals, younger individuals, and individuals with lower levels of education had higher unemployment rates and steep declines in labor force participation (Bureau of Labor Statistics, 2020b; Congressional Research Service, 2021b). Individuals with children were also disproportionately affected. School closures reduced weekly work hours among parents of school-age children by 11%–15%; mothers' labor supply was impacted particularly strongly (Amuedo-Dorantes, Marcén, Morales, and Sevilla, 2020).

The COVID-19 pandemic also changed labor dynamics when it came to work location. About 35% of the U.S. workforce worked entirely from home in May 2020, up from between 8.2% and 15% in February 2020 (Bick et al., 2020; Brynjolfsson et al., 2020). The prevalence of home-based work was not homogenous, with high-income, highly educated, and white individuals being most likely to work from home amidst the pandemic, in part due to their occupations being more suited to telework (Dingel and Neiman, 2020). Indeed, 46.5% of workers with a 4-year college degree were able to work from home before the pandemic, compared to just 9.2% of workers with only a high school diploma (White and Spell, 2020). And unsurprisingly, during the pandemic, contact-intensive industries like *accommodation and food service* and *entertainment and recreation* saw lower levels of working from home, while "desk job" oriented sectors like *finance and insurance* or *professional and business services* saw higher prevalence of remote work (Bick et al., 2020). Prevalence of home-based work also varied geographically. Using nationally representative occupation survey data, Dingel and Neiman estimated that 36% of U.S. workers had jobs that could be conducted at home; this percentage varied substantially across urban areas, being highest in Silicon Valley and Washington DC and lowest in Las Vegas. At the county-level, the share of jobs that could be done from home appeared to be lowest in rural areas (White and Spell).

Given the transition to remote work, online learning, and home-based entertainment, we would expect to see a spike in internet usage during the pandemic. Since the collective internet is composed of many smaller networks and providers, it's difficult to get a comprehensive picture of usage. We can use data from individual internet service providers (ISPs) and telecommunications industry organizations, however, to gain a rough understanding of pandemic-era internet traffic. Since March 1, 2020, NCTA – the Internet & Television Association has compiled a biweekly report that tracks traffic changes among several of its major members – Altice, CableOne, Charter, Comcast, Cox, GCI, Mediacom, Midco, and Sjoberg's. As of June 5, 2021, downstream usage had increased by 24.6% since March 1, 2020; upstream usage had increased 49.5% over the same period. A sizeable portion of this growth occurred during March 2020 – downstream use saw a 20.1% increase, while upstream use saw a 27.7% increase (NCTA – the Internet & Television Association, 2021). Another industry report, published by OpenVault, a broadband insights provider, pointed to an even larger increase in internet use. According to this report, from February 2020 to December 2020, downstream demand increased by 51.4%, while upstream demand increased by 82.4%. Again, much of this growth occurred from March to May of 2020 (OpenVault, 2021). This relatively larger increase in upstream utilization is consistent with an increase in videoconferencing. Cisco's Webex hosted more than twice as many meeting minutes in March of 2020 as February 2020, and at the height of lockdowns in Italy, Microsoft saw a 775% increase in Teams calling in the country, which required large amounts of data uploads (Robbins, 2020; Spataro, 2020).

This increase in internet usage appears to be coming, at least in part, from new internet subscribers. In the U.S., it is estimated that the top 16 largest cable and phone providers – composing 96% of the market – gained 4.9 million additional broadband subscribers in 2020, the vast majority of which (94%) were residential subscribers (Leichtman Research Group, 2021). Similar dynamics were seen across the globe. For example, Rostelecom, Russia's national telecommunications company, saw a 22% increase in requests for broadband service in March 2020 (Rostelecom, 2020).

2.2. Economic benefits of broadband

Over two decades since the introduction of broadband within the U.S. there has been a sizeable quantity of literature exploring its economic impacts – from impacts on GDP and productivity, to income and poverty, to establishment growth and entrepreneurship. Effects on GDP have been positive, with gains ranging from 0.17 to 1.5 percentage points per percentage point increase in broadband penetration (Koutroumpis, 2009; Czernich, Falck, Kretschmer, and Woessmann, 2011; Gallardo et al., 2021). Work exploring broadband's impact during SARS-era stay-at-home orders also showed a positive effect on GDP (Katz, Jung, & Callorda, 2020). Looking to income, impacts appear more mixed; high levels of broadband adoption have a positive impact on median household income, while high levels of broadband availability appear to have no impact, or potentially even a negative impact on income (Lehr et al., 2006; Whitacre et al., 2014a, 2014b). Effects on poverty have been found to be positive, with particularly large benefits occurring in rural areas (Mora-Rivera and García-Mora, 2021). Additionally, positive impacts have been found when it comes to businesses and entrepreneurs; new firms locating in rural areas were 60%–101% more likely to locate in zip codes with broadband availability (Kim and Orazem, 2016). Conroy and Low (2022) also showed that broadband positively impacts the rural establishment birth rate, particularly for nonemployer businesses.

Several studies have investigated broadband's relationship with employment metrics, the focus of this study. Much of the work surrounding broadband and employment shows a positive link between the two variables. Lehr et al. (2006) analyzed the impact of availability on total employment during broadband's initial rollout period. Using matched sample analysis, they found that communities in which broadband was available early, before the year 2000, experienced faster growth in total employment throughout 2000, 2001, and 2002. Kolko (2012) found a similar relationship during broadband's early years. Kolko's work, which used an instrumental variable approach and number of broadband providers as a proxy for availability, shows that availability's impact on growth in total employment was positive over the years 1999–2006. While these studies focus on the entirety of the United States, other work shows similar trends were occurring in rural areas.

At least one study using more contemporary data has also found that broadband availability benefits employment-related measures. Hasbi (2017) found that the presence of a high-speed broadband network (30 Mbps and up) reduced unemployment in communities in France. Hasbi's analysis, which covered the 2010 to 2015 period and utilized panel data methods, determined that high-speed broadband lowered unemployment by a large amount – approximately seven percentage points.

Other studies have found that broadband has no impact on employment measures. For example, while Kolko's 2012 study did show a positive relationship between broadband availability and total employment, it also showed that availability does not have any impact on the employment rate. This finding may suggest broadband benefits communities but may not increase the odds of any single individual finding work. Additionally, Whitacre et al. (2014a) found that though broadband adoption has a positive impact on total employment, broadband availability has no impact on total employment. This suggests that lack of demand, not lack of infrastructure, may be preventing communities from seeing benefits from broadband.

2.3. Broadband availability versus broadband adoption

The gap between availability rates and adoption rates was estimated to be 30 percentage points in metropolitan counties and 32 percentage points in nonmetropolitan (rural) counties in the U.S. in 2019 (Low et al., 2021). It follows that there are often differences in results when broadband adoption and broadband availability are used as the independent variables of interest, and the distinction may indicate where policy efforts should be targeted.

Much of the early broadband literature focused on the economic benefits of broadband availability (e.g., Kolko, 2012), which led to discussion about the digital divide in the U.S. (Warf, 2013). Subsequent work began to focus on adoption, not just availability. For example, Katz and Berry (2014) highlighted the difference between broadband availability and adoption rates using qualitative and quantitative data and Rhinesmith, Reisdorf, and Bishop (2019) learned that ability to pay for broadband corresponds closely with cultural and digital literacy barriers. Several studies concluded that subsidizing broadband subscription costs and providing digital literacy training would enhance adoption rates among elderly and low-income households (Whitacre and Rhinesmith, 2016) and those with school-age children (Rosston and Wallsten, 2020).

Econometric models have begun to shed-light, empirically, on the availability and adoption gap. Whitacre and Mills (2007) used bootstrapped decompositions of logit model to examine how people- and place-related factors and infrastructure each contributed to the rural-urban digital divide. They found that infrastructure impacts were small compared to impacts from income, network effects and education level – factors that all impact adoption and use of the internet. Using propensity score matching, Whitacre et al. (2014a) looked at the impacts of both broadband availability and broadband adoption on a wide variety of measures, including median household income, number of non-farm proprietors, non-farm proprietor income, the so-called *creative class*, number of firms, total employed, poverty, and the unemployment rate. They found that broadband adoption had a clear positive relationship with many of these measures. However, results for availability were often insignificant or took inconsistent signs. Similar results were found when using a spatial econometrics approach with many of the same dependent variables (Whitacre et al., 2014b). Gallardo et al. (2021) aimed to discover which broadband indicator was the most relevant in explaining productivity, as measured by GDP per job. Using spatial error ordinary least squares (OLS) models, the authors found that adoption-focused metrics were more closely associated with productivity than availability-focused metrics.

In summary, in all cases where adoption and availability metrics have been compared, authors have found that broadband adoption has a clearer link with positive economic impacts than broadband availability. These results suggest that availability alone is not sufficient in helping communities accrue economic benefits from broadband; supply-oriented policies are insufficient. Availability must be coupled with adoption and demand-oriented policies, such as subscription subsidies, for communities to experience broadband's benefits.

3. Hypotheses and data

This analysis of broadband's impact on employment rates during April and May 2020 – when stay-at-home orders were most prevalent – captures the impacts of broadband when the economy was the most reliant on broadband usage. It is reasonable to believe that employment was less negatively affected where business virtualization was higher. In this paper, we ask: Did rural areas with higher broadband availability have higher employment rates during this period? Were broadband adoption rates associated with employment rates in rural areas? If so, did this relationship vary by the type of technology adopted?

Given that much of the recent literature, including several analyses focused on rural counties, finds a clearer link between economic impacts and broadband adoption (Gallardo et al., 2021; Whitacre et al., 2014a, 2014b), we expected to find a similar relationship in our analysis – perhaps an even stronger relationship given the increased pandemic-era reliance on broadband. Additionally, given the prevalence of working from home during the pandemic, an activity that requires large amounts of data to be transferred, we hypothesized that the adoption of reliable high-speed internet technologies (i.e., fixed wire-type) would have a stronger relationship with the employment rate than the adoption of any internet technologies (i.e., cellular hotspots or satellite service).

The analysis is conducted at the county level. Our focus is on rural counties because availability and adoption are both lower in rural areas than urban areas (Low et al., 2021). Like less-developed countries, for which lower fixed broadband penetration has been found to hurt the economy (Katz and Jung, 2021), rural areas within the U.S. with lower broadband penetration are likely worse-off. Additionally, we are particularly interested in rural impacts given recent rural broadband-related investments, including USDA's investments in rural broadband infrastructure via its ReConnect pilot program, and the Association of Public and Land-Grant

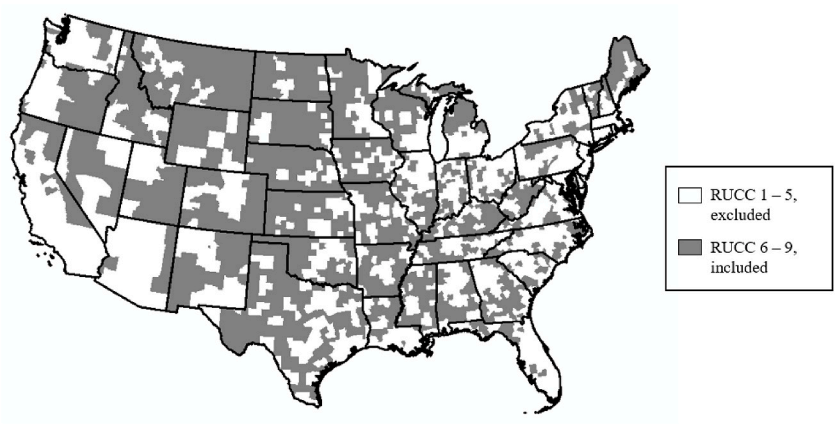

Fig. 1. Counties included in analysis.

Universities' investments in Cooperative Extension-based digital readiness. We focus on counties with fewer than 20,000 people, a cutoff promulgated by the United States Department of Agriculture's Rural-Urban Continuum Codes (RUCC), developed by its Economic Research Service. Over half of U.S. counties (53%) are included in this definition, and these counties contain 9% of the U.S. population (USDA, 2020). See Fig. 1 for a map of the counties included in our analysis.

3.1. Dependent variable

Our dependent variable is the county-level employment rate in April and May 2020. We use the employment rate rather than the unemployment rate given that during the COVID-19 pandemic many individuals dropped out of the labor force to avoid exposure to the virus, to care for children, or to supervise remote learning (Amuedo-Dorantes et al., 2020; Alon, Doepke, Olmstead-Rumsey, and Tertilt, 2020). Accordingly, our model controls for factors influencing county-level employment, such as the proportion of the population who are minors or retirement age individuals, prevalence of COVID-19, and proportion of households headed by single women with children.

The dependent variable's numerator is the average of county-level total employment in April and May, from the Bureau of Labor Statistics. The denominator is each county's 2019 population, from the U.S. Census Bureau's population estimates program. Summary statistics for our dependent variable are available in Table 1.

Table 1
Summary statistics for counties with RUCC codes six through nine.

Variable	Obs	Mean	Std. Dev.	Min	Max
aprmay_emp	1625	40.262	8.445	18.561	88.563
bb_avail	1625	81.507	21.248	0.000	100.000
bb_wired	1625	49.836	12.015	9.645	84.211
bb_any	1625	71.726	8.365	34.769	92.875
und_20	1625	24.083	3.839	7.960	44.886
ov_64	1625	21.531	4.542	7.497	43.266
pctlesshs14to18	1625	14.656	6.840	1.200	66.300
pctcolgrad14to18	1625	17.914	6.337	5.400	66.500
pct_black	1625	7.926	14.921	0.000	86.593
pct_hispanic	1625	9.083	14.272	0.663	94.710
pct_womanwchild	1625	10.327	4.665	0.000	33.898
6	1625	0.359	0.480	0.000	1.000
7	1625	0.258	0.438	0.000	1.000
8	1625	0.135	0.342	0.000	1.000
9	1625	0.249	0.432	0.000	1.000
pcinc2018	1625	41551.390	11195.780	18554.710	249694.600
gdp_growth	1625	7.443	30.478	−47.941	623.881
pop_growth	1625	−1.141	4.337	−33.333	36.843
popden	1625	28.095	26.140	0.243	177.129
na_scale	1625	−0.153	2.182	−6.400	10.750
dt100k	1625	147.647	95.149	27.220	516.086
tot_estabs	1625	447.012	354.790	11.000	2650.000
min_wage	1625	8.328	1.491	7.250	13.500
av_cases	1625	1.181	2.400	0.000	33.422
always	1625	45.252	13.888	11.500	88.900
pct_ind22	1625	0.596	1.287	0.004	28.764
pct_ind23	1625	5.681	2.486	0.446	23.840
pct_ind31	1625	8.762	7.876	0.056	65.558
pct_ind42	1625	2.539	2.097	0.019	41.847
pct_ind44	1625	9.640	2.775	1.151	49.567
pct_ind48	1625	4.350	2.408	0.156	28.823
pct_ind51	1625	0.746	0.720	0.020	14.422
pct_ind52	1625	3.828	2.756	0.074	46.302
pct_ind53	1625	3.016	1.569	0.247	15.814
pct_ind54	1625	2.870	2.023	0.235	64.511
pct_ind55	1625	0.500	0.774	0.005	9.251
pct_ind56	1625	3.275	2.115	0.172	28.685
pct_ind61	1625	1.171	1.497	0.018	14.551
pct_ind62	1625	8.409	4.189	0.098	27.007
pct_ind71	1625	1.460	1.476	0.091	21.480
pct_ind72	1625	5.797	3.138	0.130	32.116
pct_ind81	1625	6.055	1.951	0.359	30.144
pct_ind90	1625	16.330	6.854	1.614	81.997
pct_ind99	1625	0.045	0.074	0.000	1.398

3.2. Focal independent variables

We have three independent variables of interest: *broadband availability, wired broadband adoption, and any internet adoption*. *Broadband availability* is the percentage of households with access to fixed wireline broadband infrastructure with household-level speeds of at least 25/3 Mbps. Here, *fixed wireline* internet includes wire-type technologies such as fiber, cable, and digital subscriber line (DSL), and 25/3 indicates the speed threshold – internet speeds must be at least 25 Mbps for downloads and 3 Mbps for uploads. The 25/3 threshold comes from the Federal Communications Commission's (FCC's) current standard for a broadband connection. *Broadband availability* is calculated using the number of households to which fixed wireline broadband infrastructure is available, as reported by the FCC Form 477 as of December 2019, normalized by the number of households in each county. Pitfalls associated with these data are discussed below. Broadband availability, for all U.S. counties, is mapped in Fig. 2. Much of the southern U.S. has lower levels of broadband availably, while the Northeast, upper plains, West, and parts of Texas have higher broadband availability. Many of the counties with low availability appear to be rural counties, in line with the digital divide discussed in the introduction.

Our second independent variable of interest, *wired broadband adoption*, represents the percentage of households that have a paid subscription to fixed wireline broadband. The numerator – the number of households with a fixed wireline subscription – is from the five-year American Community Survey (ACS), 2015–19. The ACS simply asks about the type of technology used – cable, fiber, and DSL – and does not capture internet speeds. Thus, this measure is a proxy for fixed wireline broadband adoption, albeit a good one, since the two most common technologies, cable and fiber, are nearly always over the 25/3 speed threshold. The denominator of *wired broadband adoption* is the number of total households in each county, also from the 2015-19 ACS. *Wired broadband adoption* is mapped in Fig. 3. Like broadband availability, the southern U.S. has lower levels of wired adoption than the rest of the U.S. High levels of adoption in urban areas – the Northeast, Chicago, Atlanta, and others – can also be observed.

Our final independent variable of interest is *any internet adoption*. This variable is defined as the percentage of households that have a paid subscription to any internet technology – fixed wireline technologies but also technologies like cellular, satellite, and fixed wireless. This measure is from the same data source, is over the same period, and is calculated in the same manner as for *wired broadband adoption.*

Summary statistics for all three independent variables of interest, for the study counties, are reported in Table 1. Across our population of interest, 71.7% of households had a paid subscription to any broadband technology (*any internet adoption)*. For *wired broadband adoption*, this number was lower at 49.8%. Finally, 81.5% of households had broadband available to them (*broadband availability)*.

Our independent variables of interest are not without pitfalls. It is well documented that the FCC Form 477 data are somewhat unreliable (Grubesic, 2012; Mack, 2019; Congressional Research Service, 2021a). The primarily reason for unreliability is that a census block is reported as served if a provider does serve or *could* serve at least one location in that block. Thus, coverage is overstated in two ways: providers can include a census block if they *could* (but do not) provide service, and everyone in a census block is counted as served if at least one premises is served – in a rural context this is particularly alarming, as rural census blocks are larger than urban census blocks. This overstatement is large in magnitude. The FCC 2020 Broadband Deployment Report, based on the FCC's Form 477 dataset, concludes that 94.4% of Americans had fixed wireline broadband available at their homes as of 2018 (Federal Communications Commission, 2020). A study by BroadbandNow, a provider of industry statistics and policy analysis, investigated whether this number was accurate. Their study found that roughly 43.7 million Americans did not have in-home access to broadband in 2018 (BroadbandNow, 2021). This equates to 13.4% of the U.S. population. Thus, the FCC's data may overstate true broadband availability by approximately 7.8 percentage points. It is likely this overstatement is larger in rural areas.

The ACS data, used to assess adoption rates, also have pitfalls. For one, responses are self-reported, and individuals may not be aware of or understand what types of broadband technologies they utilize. Additionally, in rural regions, the margin of error for ACS

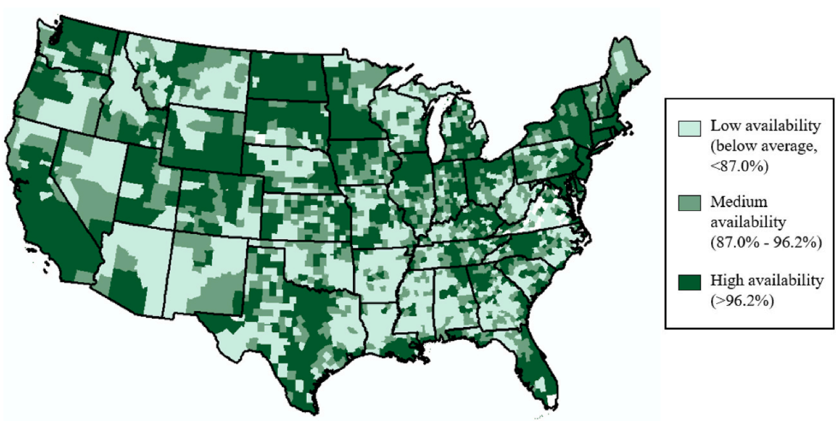

Fig. 2. Percent of households with fixed 25/3 broadband available. From December 2019 FCC Form 477.

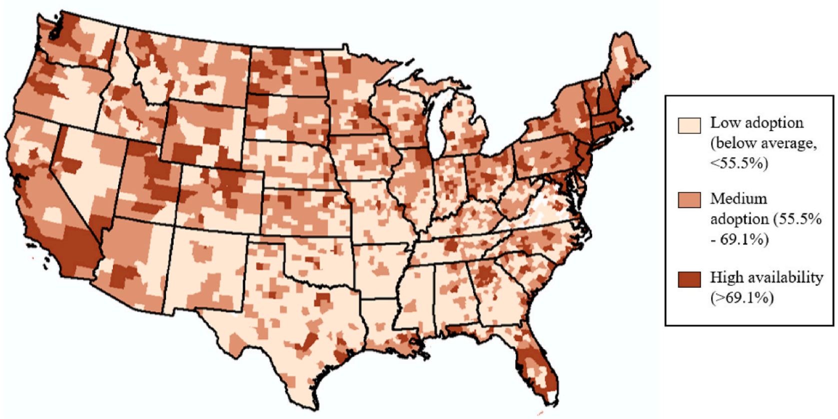

Fig. 3. Percent of households with a fixed wireline internet subscription. From 2015 to 2019 ACS.

estimates can be high due to relatively few responses. Thirdly, these data are from surveys conducted in the years 2015 through 2019, so they may not accurately represent broadband adoption rates during the pandemic, especially considering the documented increase in internet usage during the COVID-19 era.

3.3. Control variables

We use three vectors of controls in our analysis: demographics, economy and place characteristics, and COVID-19-related controls. Our demographics and economy and place characteristics vectors were chosen based on factors controlled for in similar studies. Our COVID-19-related vector largely had no precedence, given the recency of the pandemic. A complete description of controls, with sources, can be found in Table 2. Summary statistics may be found in Table 1.

Our demographic vector, Φ, includes demographic measures widely used in regional studies of economic outcomes – age, education, and race and ethnicity. These are factors by which pandemic-era employment rates have been shown to vary (Congressional Research Service, 2021b; Bureau of Labor Statistics, 2020b) and which have been controlled for in similar broadband studies (Kolko, 2012; Whitacre et al., 2014a; Lobo, Alam, and Whitacre, 2020). We also include one less common demographic control, the percentage of households headed by single mothers, since individuals with children – particularly women with children – faced labor market-related disadvantages during the pandemic (Amuedo-Dorantes et al., 2020).

Our economy and place vector, Ψ, includes measures of income and GDP, population and population density, natural amenities, drive time to the nearest city of at least 100,000 people, total number of establishments in each county, state-level minimum wage, and rurality. Again, these controls were chosen based on previous studies investigating the economic and employment impacts of broadband (Kim and Orazem, 2016; Mack, 2014; Whitacre et al., 2014b).

The third and final vector, Ω, includes COVID-19 cases per 1000 people and mask usage rates, from a county-level survey conducted by the New York Times and Dynata. Additionally, a set of controls include the percentage of employment in each major sector of the U. S. economy, as of 2020. These controls were included given that the employment rate varied widely by industry during the pandemic (Bureau of Labor Statistics, 2020b; Congressional Research Service, 2021b). The agricultural and mining sectors were the omitted condition. This category was omitted since agriculture and mining saw little to no employment impacts during the pandemic (Congressional Research Service, 2021b). Last, state-level fixed effects are included in this vector to account for the heterogeneity in COVID-19 related policies during the study period.

4. Empirical model and methods

We estimate three different models, identical but for the focal explanatory variable of interest. The three focal explanatory variables are highly correlated, and we do not have any priors about interaction effects. Thus, we estimate the following three models of the employment rate, *av_emp*, in county *i*:

$$av\_emp_i = \beta_0 + \beta_1 \mathrm{bb\_avail}_i + \beta_2 \Phi_i + \beta_3 \Psi_i + \beta_4 \Omega_i \tag{1}$$

$$av\_emp_i = \beta_0 + \beta_1 \mathrm{bb\_wired}_i + \beta_2 \Phi_i + \beta_3 \Psi_i + \beta_4 \Omega_i \tag{2}$$

$$av\_emp_i = \beta_0 + \beta_1 \mathrm{bb\_any}_i + \beta_2 \Phi_i + \beta_3 \Psi_i + \beta_4 \Omega_i \tag{3}$$

where Φ represents the demographics vector, Ψ represents the economy and place vector, and Ω represents the COVID-19-related vector. As seen in Table 2, *bb_avail* represents broadband availability, *bb_wired* represents wired broadband adoption, and *bb_any* represents any internet adoption.

Table 2
Names and descriptions of all variables, with sources.

Name	Category	Description	Source	Data Time Period
aprmay_emp	Dependent variable	Percent of population employed, average of April and May 2020	BLS, Census Bureau	April and May 2020
bb_avail	Independent variable of interest	Percent of households with access to broadband infrastructure at the home	FCC Form 477	December 2019
bb_wired	Independent variable of interest	Percent of households with a paid broadband subscription: cable, fiber, and DSL technologies	ACS	2015–2019
bb_any	Independent variable of interest	Percent of households with a paid broadband subscription: any technology	ACS	2015–2019
und_20	Demographics	Percent of population under age 20	Census Bureau	2019
ov_64	Demographics	Percent of population over age 64	Census Bureau	2019
pctlesshs14to18	Demographics	Percent of population which did not finish high school	USDA ERS	2014–2018
pctcolgrad14to18	Demographics	Percent of population which are college graduates	USDA ERS	2014–2018
pct_black	Demographics	Percent of population that is Black	Census Bureau	2019
pct_hispanic	Demographics	Percent of population that is Hispanic	Census Bureau	2019
pct_womanwchild	Demographics	Percent of households that are headed by single a single woman with children	Census Bureau	2015–2019
rucc_2013	Economy and place characteristics	Rurality, as measured by RUCC code	USDA ERS	2013
pcinc2018	Economy and place characteristics	Per capita income in 2018	BEA	2018
gdp_growth	Economy and place characteristics	Five-year growth in GDP	BEA	2013 to 2018
pop_growth	Economy and place characteristics	Five-year growth in population	Census Bureau	2014 to 2019
popden	Economy and place characteristics	Population density	Census Bureau	2019
na_scale	Economy and place characteristics	USDA ERS Natural Amenities Scale	USDA ERS	1999
dt100k	Economy and place characteristics	Drive time to nearest city of 100,000+	USDA, Esri	2015
tot_estabs	Economy and place characteristics	Total business establishments in a county	BLS QCEW	2019
min_wage	Economy and place characteristics	State-level minimum wage	Economic Policy Institute	July 2020
av_cases	Pandemic-related	Average number of COVID-19 cases per 1000 people, April and May 2020	USA Facts COVID-19 Case Database	April and May 2020
always	Pandemic-related	Percent of population that “always” wears a mask when in public	New York Times and Dynata	July 2020
pct_ind22	Pandemic-related	Percentage of employment in utilities	Emsi	2020
pct_ind23	Pandemic-related	Percentage of employment in construction	Emsi	2020
pct_ind31	Pandemic-related	Percentage of employment in manufacturing	Emsi	2020
pct_ind42	Pandemic-related	Percentage of employment in wholesale trade	Emsi	2020
pct_ind44	Pandemic-related	Percentage of employment in retail trade	Emsi	2020
pct_ind48	Pandemic-related	Percentage of employment in transportation and warehousing	Emsi	2020
pct_ind51	Pandemic-related	Percentage of employment in information	Emsi	2020
pct_ind52	Pandemic-related	Percentage of employment in finance and insurance	Emsi	2020
pct_ind53	Pandemic-related	Percentage of employment in real estate rental and leasing	Emsi	2020
pct_ind54	Pandemic-related	Percentage of employment in professional, scientific, and technical services	Emsi	2020
pct_ind55	Pandemic-related	Percentage of employemt in management	Emsi	2020
pct_ind56	Pandemic-related	Percentage of employment administrative and support	Emsi	2020
pct_ind61	Pandemic-related	Percentage of employemt in educational services	Emsi	2020
pct_ind62	Pandemic-related	Percentage of employment in health care and social assistance	Emsi	2020
pct_ind71	Pandemic-related	Percentage of employemt in arts, entertainment, and recreation	Emsi	2020
pct_ind72	Pandemic-related	Percentage of employemt in accomodation and food services	Emsi	2020
pct_ind81	Pandemic-related	Percentage of employemt in other services	Emsi	2020
pct_ind90	Pandemic-related	Percentage of employment in public administration	Emsi	2020
pct_ind99	Pandemic-related	Percentage of employment in “unclassified"	Emsi	2020

We estimate all three equations using three different estimators for each: OLS, weighted least squares (WLS), and two-stage least squares. OLS was initially used. Based on visual inspection of plots and the White test for heteroskedasticity, we also utilized the WLS estimator, which produces efficient estimates when the assumption of homoskedasticity is violated.

The two-stage least squares method is the primary focus of this section. This estimator is used to address endogeneity and to allow for causal interpretations of the regression results. Endogeneity in our models could be coming from two sources: omitted variable bias or reverse causality. We do control for a wide variety of factors; however, given the complexity of rural economies and the further nuances introduced by the COVID-19 pandemic, there are likely omitted factors, nonetheless. Reverse causality is also a concern, as the employment rate could be affecting broadband availability and adoption. When ISPs conduct market analysis and determine which locations to serve, they consider economic dynamics and expectations for an area – ISPs locate in markets where consumers can afford their services (Grubesic, 2004; Whitacre and Mills, 2007). Thus, this could mean a higher employment rate indirectly induces broadband availability. Additionally, the employment rate could be impacting broadband adoption. Lack of need for the technology is a major reason why individuals report not adopting broadband (Lee and Whitacre, 2017). Given the increase in home-based work during the pandemic, those who are employed are more likely to have a need for broadband. Thus, higher rates of employment at the county level could be increasing the broadband adoption rate.

Ideally, instrumental variables should be correlated with the independent variable of interest, our broadband measures, yet

Table 3
Results from preferred models.

Variables	Model I: Broadband Availability	Model II: Wired Broadband Adoption	Model III: Any Internet Adoption
bb_avail	0.368***		
	(0.0828)		
bb_wired		0.869***	
		(0.200)	
bb_any			1.822***
			(0.502)
und_20	−0.00841	0.224*	0.417**
	(0.124)	(0.122)	(0.177)
ov_64	−0.168*	0.155	0.593***
	(0.0969)	(0.116)	(0.229)
pctlesshs14to18	−0.224***	0.000265	0.440**
	(0.0815)	(0.0919)	(0.215)
pctcolgrad14to18	0.119*	−0.105	−0.218
	(0.0721)	(0.104)	(0.148)
pct_black	0.0660*	0.135***	0.150***
	(0.0368)	(0.0446)	(0.0575)
pct_hispanic	0.0194	−0.0111	0.0340
	(0.0355)	(0.0383)	(0.0496)
pct_womanwchild	−0.223**	0.124	0.236
	(0.104)	(0.125)	(0.171)
7.rucc_2013	−0.295	−0.992*	−0.392
	(0.499)	(0.536)	(0.691)
8.rucc_2013	2.410**	1.607*	2.298*
	(0.950)	(0.893)	(1.191)
9.rucc_2013	1.065	−0.152	0.773
	(0.782)	(0.770)	(0.975)
pcinc2018	0.000158***	5.68e-05*	5.40e-07
	(4.91e-05)	(3.18e-05)	(5.67e-05)
gdp_growth	0.0169**	0.0245***	0.0341***
	(0.00807)	(0.00866)	(0.0119)
pop_growth	0.0656	0.232**	0.121
	(0.0771)	(0.0968)	(0.0981)
popden	−0.0653***	−0.0487**	−0.0923***
	(0.0210)	(0.0192)	(0.0316)
na_scale	0.0220	0.00857	−0.194
	(0.197)	(0.207)	(0.228)
dt100k	0.00655*	−0.00365	0.0129**
	(0.00379)	(0.00438)	(0.00585)
tot_estabs	−4.33e-05	−0.000615	−0.000405
	(0.000816)	(0.000928)	(0.00113)
min_wage	−2.112	−7.693***	−7.316***
	(1.420)	(1.960)	(2.319)
av_cases	−0.0414	−0.224**	−0.386**
	(0.0786)	(0.0869)	(0.160)
always	0.0136	0.0724**	0.108**
	(0.0244)	(0.0290)	(0.0449)
Constant	42.93***	57.46***	−54.31
	(14.24)	(13.95)	(35.97)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.176	0.131	.

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

uncorrelated with each model's error term. Thus, we use several terrain-related measures as instrumental variables, like the approach used by Kolko (2012), in which average slope of local terrain was used as an instrument, and Conroy and Low (2022), in which a land developability index and a proxy for slope were used as instruments. Our potential terrain-related measures included topography and the percent of a county's area that is covered in each of the following: perennial snow and ice, barren or rocky land, forest, and wetland.

Terrain-related measures satisfy the instrument relevancy assumption – terrain measures are expected to have a direct relationship with the broadband availability rate. Low return on investment for ISPs – for which high costs are a factor – is a major barrier to wider availability (Kolko, 2012; Prieger, 2003). In turn, type of terrain is a major factor determining installation cost – installing broadband on steep terrain, rocky terrain, wet terrain, terrain with many trees and roots, or icy and snowy terrain is difficult and costly (Kolko, 2012). Even when poles are already in-place, pole attachment fees levied by incumbent telephone or electricity providers reflect these higher installation costs. Thus, we would expect higher values for our terrain measures to be correlated with lower levels of broadband availably. Since broadband availability is necessary for adoption, we also expect our terrain measures have a negative correlation with broadband adoption, though less strong than for broadband availability. This can indeed be seen in the first-stage results of our two-stage least squares regressions (Table A.4).

The instrument exogeneity assumption is more difficult to satisfy. Terrain is largely predetermined by geological forces, so we can be sure the employment rate is not affecting terrain. However, terrain may have an impact on the employment rate, particularly through its impact on the type and intensity of an area's economic activity. Our inclusion of industry controls mitigates this impact, however. Additionally, the inclusion of state-level fixed effects accounts for additional unobservables. Moreover, as mentioned above, terrain-related instruments have successfully been used in past work (Kolko, 2012; Conroy & Low, 2022), suggesting instrument endogeneity may not be a concern.

Looking at the correlations between each of our instruments and each of our independent variables of interest, it appears that *forest* and *wetland* are the strongest instruments for our broadband measures; these variables have correlations of between −0.17 and −0.25 with each of our three broadband measures, while the other measures of terrain have correlations that are closer to zero. As an additional test of instrument strength, we preliminarily estimated each model using one instrument at a time, examining post-estimation results. The only instruments that were strong, defined by the Staiger and Stock F-statistic cutoff of ten, in at least one model were *forest* and *wetland.* Therefore, *forest* and *wetland* were both used as instruments for the broadband measures in the two-stage least squares results presented. Data for both are from the 2016 National Land Cover Database (United States Geological Survey, 2020).

5. Results

Our results suggest that during the height of COVID-19-related disruptions, higher wireline broadband availability and higher wireline broadband adoption led to higher employment rates in rural areas of the U.S. Results surrounding the impact of *any internet adoption* on employment rates are inconclusive.

5.1. Focal variable results – broadband availability and adoption

Equations (1)–(3) were estimated using OLS (Table A.1), WLS (Table A.2) and 2SLS (Table 3 and Table A.3). Results for the first stage of two-stage least squares are available inTable A.4. Post-estimation tests helped us determine which estimator was preferred for each independent variable of interest. Testing for endogeneity of *broadband availability*, we obtained a p-value of less than 0.001 indicating that endogeneity is highly likely. Additionally, the F-statistic when testing strength of instruments is 15.4, above the rule-of-thumb threshold of ten (Staiger and Stock, 1997) and over the more conservative bias-related thresholds computed in Stock and Yogo (2005). Thus, given we have evidence that a two-stage least squares approach is warranted due to endogeneity, and that *forest* and *wetland* are not weak instruments for *broadband availability*, we conclude that two-stage least squares is the preferred estimator for *broadband availability*.

Looking at the two-stage least squares model, we can conclude that *broadband availability* had a positive impact on the employment rate in rural areas during the pandemic (Table 3, model I). Its coefficient is 0.368 (p-value < 0.001), indicating that a one percentage point increase in broadband availability increased the employment rate by 0.368 percentage points. Given the mean employment rate (40.30%) and mean broadband availability (81.52%), this impact does appear to be economically significant, as well as statistically significant at the 1% level.

Two-stage least squares is also the preferred estimator for wired broadband adoption. Testing for endogeneity of *wired broadband adoption*, we obtained a p-value of less than 0.001, again indicating that endogeneity is highly likely. Additionally, with an F-statistic of 12.68, *forest* and *wetland* are strong instruments for wired adoption.

Its coefficient is 0.869, indicating that a one percentage point increase in wired broadband adoption increased the employment rate by 0.869 percentage points (Table 3, model II). This is somewhat large, but not unreasonably so in the context of rural wired broadband adoption rates. As discussed in the introduction, the level of wired broadband adoption has been persistently low in many rural communities – the average is around 50% in our dataset, for example. Thus, even a few percentage points increase in the wired broadband adoption rate may represent a major achievement for a community, making this coefficient seem more reasonable. Further, wireline broadband availability is a prerequisite for wireline adoption, so the point estimate on adoption likely reflects some of the availability effect (we could not control for availability in the adoption models without inducing problematic levels of multicollinearity).

Results for *any internet adoption* are inconclusive, at least using two-stage least squares and WLS estimators. Two-stage least squares is not a preferred estimator for *any internet adoption*. Testing for endogeneity of the variable, we obtained a p-value of less than 0.001. Thus, *any internet adoption* is likely endogenous. However, with an F-statistic of only 6.99, *forest* and *wetland* are weak instruments. This is perhaps not surprising, as *any internet adoption* includes wireless technologies, such as cellular, satellite and fixed wireless, whose availability is generally independent of terrain. Moreover, the coefficient on *any internet adoption* is 1.822, over twice the size of our coefficient for *wired broadband adoption*, and implausibly large (Table 3, model III). These results suggest the econometric assumptions needed to implement the two-stage least squares estimator are violated in the case of *any internet adoption*.

We also examine the WLS case to see if this may be a more appropriate estimator for *any internet adoption*. Given the high likelihood that *any internet adoption* is endogenous ($p < 0.001$) the coefficients generated using the WLS estimator will be biased. The coefficient in the WLS model is 0.054 (Table A.2, model IX), implausibly low considering the results for availability and wired adoption. Thus, it is clear that the assumptions needed to implement the WLS procedure are also violated. Without stronger instruments, no conclusions for *any internet adoption* can be drawn. Alternatively, a different econometric approach could be used.

The wired adoption results are largely in line with recent literature discussed in our literature review (e.g., Whitacre et al., 2014a, b). The availability results run contrary to recent findings, though are more in line with results of studies examining broadband's impacts during its early years, when infrastructure was sparce – as it is today in small rural areas (e.g., Kolko, 2012). This discrepancy may be due to the wide variety of methods and estimators used throughout the literature. Changes in broadband availability data over time could also be impacting results, as the FCC has changed its speed threshold for broadband several times, and the way the data has been aggregated and reported has also varied (Mack, 2019). Considering the documented spike in internet use during the pandemic, it is also plausible that broadband adoption rates became much closer to broadband availability rates, effectively making availability a proxy for adoption. If we believe broadband use (and not the mere presence of broadband infrastructure) is the true mechanism through which benefits occur, this could explain why availability again became significant. This explanation cannot be confirmed, though, until newer ACS data become available. Only pre-pandemic data are available as of this writing.

Longer-term shifts in broadband supply- and demand-related factors could also be contributing to this discrepancy. Demand increased with the advent of social media, rise in remote work, and other realities of the 21st century. On the supply-side, ISPs have been incentivized to provide service to areas with the highest anticipated "take rates" (Low et al., 2021). Now, as the most profitable markets have been served, ISPs are expanding into marginally profitable areas, including rural areas, often with government support. Thus, we expect there to be a larger gap between broadband adoption in recent years compared to earlier in the broadband rollout period – indeed, in our dataset, there is currently a 30-percentage point difference between the availability of wired broadband and the adoption of those technologies. Therefore, it is possible that during the early stages of broadband rollout, availability was a closer proxy for adoption, leading to a significant relationship between broadband availability and various economic indicators during that period.

In sum, our results suggest that low rates of fixed, wire-type broadband availability and adoption may still be barriers to realizing economic benefits of broadband in rural America. Moreover, it's clear that these two dimensions work in tandem. Households cannot adopt broadband until the technology is available, but as stated above, ROI considerations often prevent ISPs from investing in an area until they are sure a certain portion of the population will adopt. The issue of availability thus could be mitigated through public funding or by inducing demand.

5.2. Robustness checks

Results are largely robust to an alternative, broader, definition of rurality (Table A.5). Our primary analysis focused on small rural counties, i.e., those with a population below 20,000 (RUCC 6, 7, 8 and 9). To test the robustness of our results to larger counties, we conducted the analysis on all non-metro counties (RUCC 4 through 9). The two-stage least squares estimates for *broadband availability* and *wired broadband adoption* are nearly identical across the different definitions of rural: 0.368 versus 0.351 for *broadband availability* and 0.869 versus 0.890 for *wired broadband adoption.* Both remain significant at the 1% level. The coefficient on *any internet adoption* remains implausibly large, and instruments remain weak.

These results suggest that broadband dynamics affecting the employment rate are similar in both the smallest rural places and all rural, or nonmetropolitan, counties in the U.S. Specifically, the impacts of broadband availability and wired adoption remain quite stable across both geographies, increasing our confidence in the main results.

Additionally, we conducted our analysis using the unemployment rate as the dependent variable instead of the employment rate (Table A.6). Results align with our main conclusions – *broadband availability* reduces the unemployment rate by about 0.2 percentage points, while *wired broadband adoption* reduces the unemployment rate by a larger proportion, about 0.5 percentage points. At over -1.0, the coefficient on *any internet adoption* remains implausibly large. These results suggest that even when we do not account for the percentage of the population that has dropped out of the labor force – as is captured in the employment rate – broadband availability and adoption had a positive impact on the employment situation.

As a final robustness check, we ran our analyses with a different dependent variable – the January and February 2020 employment rate, representing the period immediately preceding the pandemic (Table A.7). Compared to results using the April/May employment rate, we see minor decreases in the January/February coefficients on *broadband availability* (down 1.9%) and *wired broadband adoption* (down 1.3%). Although this difference may not be statistically significantly different than zero, these small differences were robust to our various estimators and model specifications. Results suggest that we do not have evidence to claim that the impacts of broadband on employment rates were greater at the beginning of the pandemic than just before the pandemic; however, results suggest broadband was important for rural employment rates prior to the pandemic as well as during its infancy.

5.3. Results for controls

The inclusion of a wide variety of controls in our models, especially the inclusion of industry controls and state-level fixed effects, results in a high degree of multicollinearity among these control variables. Many have a variance inflation factor value of five, ten, or even >20 in the case of our industry and state variables. Thus, the standard errors and sometimes even coefficient sign on many of our controls fluctuate from model to model.

In the context of this paper, multicollinearity is not a concern, as we are interested solely in broadband-related impacts. We prioritized including a wide variety of controls to ensure the coefficients on our independent variables of interest were as accurate as possible. This accuracy, however, came at the expense of reliable coefficients on our control variables. Therefore, we do not discuss these coefficients and we suggest readers interpret these coefficients with a degree of skepticism.

Separately, it is important to note that multicollinearity is not a concern for our variables of interest. Variance inflation factors were between one and three for our broadband variables.

6. Policy implications

Results suggest that both broadband availability and wire-type adoption had positive, statistically significant, and economically significant impacts on the employment rates in rural America during the COVID-19 pandemic. Results for adoption, more broadly defined, were inconclusive. Although recent literature has found the economic benefits of broadband to be driven by adoption rates (e.g., Gallardo et al., 2021; Whitacre et al., 2014a; Whitacre et al., 2014b), our results suggest that in the most rural contexts both infrastructure investment and efforts to increase adoption rates will positively impact employment rates. Results also suggest broadband was important for rural employment rates prior to the pandemic.

Our results suggest that infrastructure availability remains a limiting factor in rural America. The U.S. is on the verge of a massive Federal broadband infrastructure investment, however, with the recent passage of the *Infrastructure Investment and Jobs Act*. The act appoints around $1 trillion for infrastructure and of that, $65 billion for broadband, with the majority, over $40 billion, designated for states to invest in broadband infrastructure development in unserved and underserved communities (Bustillo, 2021). State-level control of technology neutral dollars gives communities and regions control on how the investments are made (i.e., they may deploy stop-gap solutions such as fixed-wireless as they wait for fiber installation). This Federal investment should create faster and more reliable internet in rural communities by inducing ISPs to serve less profitable markets (Whitacre and Gallardo, 2020), and $40 billion should make a dent in total need (Low, 2020). Roll-out, however, will not be quick or straightforward due to tight labor market conditions and supply-chain issues, such as fiber cable shortages.

Federal investment, however, is not necessarily essential to incent infrastructure investment. Research suggests lower-cost ways to increase infrastructure include reducing municipal broadband provision restrictions (Whitacre and Gallardo, 2020), incentivizing the establishment of broadband cooperatives (Schmit and Severson, 2021), and establishing public-private partnerships and community-led initiatives (Lattemann, Stieglitz, Kupke, & Schneider, 2009). Further, Whitacre and Gallardo (2020) report that as of 2018, 18 states had broadband expansion spending programs and 25 states had broadband directors – these states may be better prepared to utilize the Federal funds due to their existing programmatic infrastructure. Several states are providing technical assistance for community-led broadband planning through Cooperative Extension, and Low (2020) noted that, with local input and buy-in, these efforts may complement Federal infrastructure investment.

As our findings suggest, increasing wired broadband adoption may also have economic benefits for rural communities, in addition to the benefits from infrastructure availability. Adoption policy can be effective at the local, state and Federal levels. All three levels will benefit from the *Infrastructure Investment and Jobs Act's* Digital Equity Act provision, a five-year, $2.7 billion investment in developing and implementing digital equity plans and digital inclusion. Digital literacy – teaching people how the internet can enhance their quality of life, how to use computers, and how to avoid risks such as viruses and credit card scams – can increase internet demand and be an effective adoption strategy, especially for the elderly (Lee and Whitacre, 2017; Whitacre and Rhinesmith, 2016). The Cooperative Extension efforts mentioned above also include digital literacy education efforts.

Getting rural workers and rural businesses to utilize the internet more fully should also enhance adoption. Low income individuals are less likely to have broadband and, combining this with Dingel and Neiman's (2020) work that suggests low-wage jobs are least likely to be remote, we can see why adoption could plateau in rural America. Together with broadband availability, getting business set-up for remote work and e-commerce should increase adoption and maximize the economic benefits of broadband.

Finally, the U.S. began subsidizing broadband subscriptions for low-income households during the pandemic with the hopes of boosting rural broadband adoption, as rural households have long had higher poverty rates compared to urban households (Pender, 2019). The pandemic-era temporary $50 per month Emergency Broadband Benefit (EBB) led to fewer new subscribers in low-income areas, suggesting that the households who could benefit the most are not doing so (Wallsten, 2021). Our Extension work has found potential participants were worried about being stuck in a multi-year contract with an ISP, only for the benefit to expire, suggesting the subsidy may have been more effective at increasing adoption if the program had been permanent. The *Infrastructure Investment and Jobs Act* provides just over $14 billion for the Affordable Connectivity Fund, which will provide a $30 per month subsidy with more certainty, for five years. We look forward to studies evaluating the effectiveness of the EBB and suggesting what might make the infrastructure bill's subsidy more effective.

7. Conclusion

Our results showed that broadband availability and wired broadband adoption had positive, statistically significant and economically significant impacts on rural employment rates during the COVID-19 pandemic. Results for any internet adoption were inconclusive. Results are robust to an alternate, more urban, definition of rural and using the more traditional unemployment rate as the dependent variable.

This paper makes several contributions to the literature. First, we conducted the analysis using a broadband adoption measure, *wired broadband adoption*, not yet explored in the literature. Additionally, our analysis used two relatively novel instruments for broadband, percent of land in forest and wetland. Most importantly, this paper examined the dynamics surrounding broadband and the employment rate during the COVID-19 pandemic, a time when broadband was more important to activities like commerce and work than ever before. This perspective allowed us to draw important policy implications that support on-going Federal, state and local efforts in the U.S.

This paper was not without pitfalls, however. For one, we cannot draw concrete conclusions regarding how broadband's impact on the employment rate *changed* from pre-pandemic to pandemic-era. Alternative methods, such as using a first-differenced dependent variable, could allow these types of conclusions to be made. Finding strong instruments for *any internet adoption* was also a challenge. Future work could further explore instruments for this variable; in the likely case that none can be found, an alternative estimator could be utilized to tease out the impacts of this variable on the employment rate. Spatial econometric methods could also be explored, as broadband availability is spatially dependent (Mack et al., 2011; Mack and Faggian, 2013; Whitacre et al., 2014b). Finally, we see an opportunity for additional research on the future of remote work in rural America. With rural occupations being less conducive to remote work (White and Spell, 2020) and much unknown about rural business virtualization, employment and the digital divide could become synonymous.

Funding

This work was supported by the Missouri Agricultural Experiment Station and University of Missouri Extension.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Acknowledgements

The authors wish to acknowledge support from the Missouri Agricultural Experiment Station and University of Missouri Extension, with long-term support from USDA NIFA through the Enhancing Rural Economic Opportunities (NE1749) regional research committee. The authors also thank three anonymous referees for valuable comments, Dr. Alyssa Carlson, and participants at the 2021 Southern Regional Science Association virtual meetings for comments on an earlier draft.

Appendix

Table A.1
OLS Results

Variable	Model IV: Broadband Availability	Model V: Wired Broadband Adoption	Model VI: Any Internet Adoption
bb_avail	0.0101		
	(0.00731)		
bb_wired		0.0128	
		(0.0201)	
bb_any			0.109***
			(0.0323)
und_20	0.121	0.126	0.142*
	(0.0815)	(0.0822)	(0.0818)
ov_64	−0.0893	−0.0835	−0.0465
	(0.0664)	(0.0677)	(0.0691)
pctlesshs14to18	−0.208***	−0.204***	−0.169***
	(0.0467)	(0.0457)	(0.0456)
pctcolgrad14to18			

(*continued on next page*)

Table A.1 (*continued*)

Variable	Model IV: Broadband Availability	Model V: Wired Broadband Adoption	Model VI: Any Internet Adoption
	0.218***	0.216***	0.195***
	(0.0454)	(0.0468)	(0.0470)
pct_black	−0.00465	−0.00456	0.00273
	(0.0192)	(0.0189)	(0.0184)
pct_hispanic	0.0691***	0.0693***	0.0684***
	(0.0214)	(0.0216)	(0.0212)
pct_womanwchild	−0.200***	−0.195***	−0.174***
	(0.0628)	(0.0631)	(0.0621)
7.rucc_2013	−0.402	−0.414	−0.404
	(0.323)	(0.322)	(0.320)
8.rucc_2013	0.151	0.110	0.220
	(0.450)	(0.450)	(0.448)
9.rucc_2013	0.0994	0.0688	0.114
	(0.475)	(0.476)	(0.470)
pcinc2018	0.000135***	0.000133***	0.000127***
	(4.64e-05)	(4.64e-05)	(4.30e-05)
gdp_growth	0.0166*	0.0167*	0.0176*
	(0.00942)	(0.00948)	(0.00949)
pop_growth	0.00570	0.00736	0.0110
	(0.0533)	(0.0539)	(0.0512)
popden	−0.00374	−0.00269	−0.00739
	(0.00932)	(0.00928)	(0.00922)
na_scale	−0.361***	−0.366***	−0.361***
	(0.121)	(0.120)	(0.118)
dt100k	0.00337	0.00318	0.00386
	(0.00242)	(0.00243)	(0.00241)
tot_estabs	0.000699	0.000701	0.000653
	(0.000529)	(0.000530)	(0.000530)
min_wage	−1.906**	−1.986**	−2.224**
	(0.890)	(0.917)	(0.900)
av_cases	−0.0651	−0.0681	−0.0849*
	(0.0505)	(0.0502)	(0.0500)
always	0.00728	0.00807	0.0131
	(0.0151)	(0.0150)	(0.0148)
Constant	56.41***	56.80***	50.15***
	(8.244)	(8.314)	(8.350)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.697	0.696	0.701

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

Table A.2
Weighted least squares results

Variables	Model VII	Model VIII	Model IX
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
bb_avail	0.00743		
	(0.00707)		
bb_wired		−0.00587	
		(0.0165)	
bb_any			0.0544**
			(0.0227)
und_20	0.0643	0.0606	0.0381
	(0.0637)	(0.0599)	(0.0613)
ov_64	−0.183***	−0.199***	−0.211***
	(0.0658)	(0.0579)	(0.0622)
pctlesshs14to18	−0.230***	−0.239***	−0.185***
	(0.0357)	(0.0337)	(0.0348)
pctcolgrad14to18	0.185***	0.192***	0.205***
	(0.0377)	(0.0380)	(0.0410)
pct_black	−0.000655	−0.00225	0.00385
	(0.0158)	(0.0149)	(0.0148)
pct_hispanic	0.0722***	0.0727***	0.0589***
	(0.0187)	(0.0177)	(0.0179)
pct_womanwchild	−0.201***	−0.200***	−0.181***
	(0.0482)	(0.0453)	(0.0467)

(*continued on next page*)

Table A.2 (*continued*)

Variables	Model VII	Model VIII	Model IX
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
7.rucc_2013	−0.299	−0.249	−0.243
	(0.262)	(0.246)	(0.252)
8.rucc_2013	−0.0422	−0.151	0.128
	(0.392)	(0.374)	(0.391)
9.rucc_2013	0.0614	−0.0779	0.0585
	(0.439)	(0.422)	(0.430)
pcinc2018	0.000199***	0.000206***	0.000208***
	(2.49e-05)	(2.57e-05)	(2.59e-05)
gdp_growth	0.0164***	0.0172***	0.0167***
	(0.00583)	(0.00588)	(0.00574)
pop_growth	−0.00661	−0.0164	−0.00571
	(0.0441)	(0.0431)	(0.0434)
popden	0.00212	0.00485	0.00275
	(0.00675)	(0.00635)	(0.00664)
na_scale	−0.216**	−0.211**	−0.186*
	(0.110)	(0.102)	(0.103)
dt100k	0.00294	0.00252	0.00362*
	(0.00193)	(0.00180)	(0.00190)
tot_estabs	0.000456	0.000389	0.000308
	(0.000374)	(0.000349)	(0.000367)
min_wage	−1.977**	−2.104**	−2.176***
	(0.846)	(0.819)	(0.810)
av_cases	−0.0663	−0.0506	−0.0602
	(0.0492)	(0.0468)	(0.0473)
always	−0.00591	−0.00730	−0.00159
	(0.0131)	(0.0120)	(0.0122)
Constant	59.73***	62.15***	57.84***
	(7.641)	(7.188)	(7.181)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.773	0.771	0.772

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

Table A.3
Industry control results for two-stage least squares regressions

Variable	Model I	Model II	Model III
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
pct_ind22	0.00452	0.216	−0.175
	(0.176)	(0.301)	(0.277)
pct_ind23	−0.0458	−0.0504	−0.272*
	(0.115)	(0.115)	(0.161)
pct_ind31	0.0249	0.0519	0.0118
	(0.0430)	(0.0429)	(0.0537)
pct_ind42	−0.131	−0.116	−0.137
	(0.114)	(0.122)	(0.140)
pct_ind44	−0.0719	−0.133	−0.0382
	(0.196)	(0.244)	(0.258)
pct_ind48	0.102	0.0679	0.0267
	(0.0963)	(0.0995)	(0.127)
pct_ind51	−0.674**	−1.623***	−0.959**
	(0.305)	(0.492)	(0.478)
pct_ind52	−0.134	−0.211**	−0.254**
	(0.0924)	(0.0915)	(0.121)
pct_ind53	−0.979***	−1.164***	−1.521***
	(0.227)	(0.256)	(0.350)
pct_ind54	−0.189	−0.214	−0.0494
	(0.119)	(0.145)	(0.157)
pct_ind55	−0.0622	0.290	0.375
	(0.251)	(0.273)	(0.331)
pct_ind56	−0.0821	−0.205	−0.0120
	(0.147)	(0.141)	(0.154)
pct_ind61	−0.219	−0.274**	0.147
	(0.140)	(0.136)	(0.220)

(*continued on next page*)

Table A.3 (*continued*)

Variable	Model I	Model II	Model III
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
pct_ind62	−0.303***	−0.305***	−0.155*
	(0.0720)	(0.0756)	(0.0898)
pct_ind71	0.317	0.0304	0.285
	(0.214)	(0.182)	(0.228)
pct_ind72	−0.280**	−0.0644	0.106
	(0.119)	(0.114)	(0.142)
pct_ind81	−0.115	0.0722	−0.0125
	(0.153)	(0.160)	(0.164)
pct_ind90	−0.213***	−0.284***	−0.181***
	(0.0556)	(0.0586)	(0.0671)
pct_ind99	6.074	4.030	4.891
	(4.149)	(3.876)	(4.702)
Observations	1625	1625	1625
R-squared	0.176	0.131	.

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

Table A.4
First stage results, corresponding to the two-stage least squares models

Variable	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
forest	−0.145***	−0.0681***	−0.0356***
	(0.0317)	(0.0143)	(0.00971)
wetland	−0.242***	−0.0914***	−0.0309
	(0.0691)	(0.0322)	(0.0248)
und_20	0.232	−0.173	−0.190**
	(0.255)	(0.109)	(0.0846)
ov_64	0.165	−0.300***	−0.381***
	(0.194)	(0.0934)	(0.0658)
pctlesshs14to18	0.141	−0.193***	−0.331***
	(0.164)	(0.0679)	(0.0532)
pctcolgrad14to18	0.218	0.351***	0.231***
	(0.142)	(0.0603)	(0.0435)
pct_black	−0.200**	−0.169***	−0.0937***
	(0.0804)	(0.0319)	(0.0253)
pct_hispanic	0.0404	0.0489	−0.00257
	(0.0766)	(0.0312)	(0.0275)
pct_womanwchild	0.0435	−0.383***	−0.245***
	(0.212)	(0.0916)	(0.0683)
7.rucc_2013	−0.203	0.711	0.00491
	(1.089)	(0.497)	(0.368)
8.rucc_2013	−6.089***	−1.656**	−1.172**
	(1.866)	(0.765)	(0.530)
9.rucc_2013	−2.354	0.407	−0.317
	(1.667)	(0.729)	(0.512)
pcinc2018	−7.33e-05	8.45e-05**	7.10e-05*
	(6.45e-05)	(4.20e-05)	(3.91e-05)
gdp_growth	0.00189	−0.00764	−0.00876**
	(0.0150)	(0.00750)	(0.00391)
pop_growth	−0.0735	−0.218***	−0.0411
	(0.170)	(0.0713)	(0.0544)
popden	0.141***	0.0400***	0.0430***
	(0.0317)	(0.0147)	(0.00979)
na_scale	−0.730*	−0.260	0.00910
	(0.408)	(0.192)	(0.123)
dt100k	−0.00836	0.00793**	−0.00555**
	(0.00785)	(0.00369)	(0.00265)
tot_estabs	0.00288	0.00189**	0.000788
	(0.00185)	(0.000878)	(0.000576)
min_wage	1.369	7.075***	3.215***
	(3.650)	(1.476)	(0.959)
av_cases	−0.136	0.153**	0.164**
	(0.192)	(0.0770)	(0.0752)
always	−0.00782	−0.0715***	−0.0542***
	(0.0551)	(0.0235)	(0.0173)
Constant	40.83	0.472	61.44***
	(34.72)	(14.07)	(9.624)
State Fixed Effects	Yes	Yes	Yes

(*continued on next page*)

Table A.4 (*continued*)

Variable	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.371	0.627	0.628

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

Table A.5
Robustness check results – alternative definition of rural (RUCCs 4 through 9)

Variables	Model X: Broadband Availability	Model XI: Wired Broadband Adoption	Model XII: Any Internet Adoption
bb_avail	0.351***		
	(0.0708)		
bb_wired		0.890***	
		(0.192)	
bb_any			1.871***
			(0.510)
und_20	−0.0676	0.207*	0.347**
	(0.114)	(0.117)	(0.168)
ov_64	−0.190**	0.156	0.566**
	(0.0862)	(0.112)	(0.224)
pctlesshs14to18	−0.195***	0.0556	0.533**
	(0.0715)	(0.0898)	(0.230)
pctcolgrad14to18	0.161***	−0.0550	−0.121
	(0.0578)	(0.0879)	(0.121)
pct_black	0.0636**	0.127***	0.141***
	(0.0321)	(0.0404)	(0.0548)
pct_hispanic	0.0188	−0.0207	−0.00615
	(0.0286)	(0.0344)	(0.0523)
pct_womanwchild	−0.209**	0.138	0.281
	(0.0922)	(0.120)	(0.177)
5.rucc_2013	0.133	−0.0102	−0.658
	(0.726)	(0.929)	(1.367)
6.rucc_2013	1.245**	2.943***	1.535
	(0.583)	(0.893)	(1.022)
7.rucc_2013	1.143*	1.919**	1.305
	(0.651)	(0.854)	(1.134)
8.rucc_2013	4.280***	5.166***	4.820***
	(1.192)	(1.474)	(1.804)
9.rucc_2013	2.932***	3.176***	3.214**
	(1.009)	(1.185)	(1.524)
pcinc2018	0.000144***	4.05e-05	−1.79e-05
	(4.37e-05)	(3.01e-05)	(5.79e-05)
gdp_growth	0.0165**	0.0239***	0.0344***
	(0.00774)	(0.00853)	(0.0121)
pop_growth	0.0383	0.209**	0.0559
	(0.0673)	(0.0862)	(0.0896)
popden	−0.0222**	−0.0274**	−0.0437***
	(0.00905)	(0.0107)	(0.0169)
na_scale	−0.0283	−0.0625	−0.154
	(0.159)	(0.177)	(0.211)
dt100k	0.00849**	−0.000735	0.0144**
	(0.00341)	(0.00392)	(0.00567)
tot_estabs	0.000426	0.000219	0.000302
	(0.000358)	(0.000475)	(0.000594)
min_wage	−2.070*	−7.204***	−6.428***
	(1.235)	(1.784)	(2.110)
av_cases	0.00291	−0.154**	−0.328**
	(0.0657)	(0.0711)	(0.136)
always	0.0170	0.0696***	0.124***
	(0.0208)	(0.0267)	(0.0471)
Constant	44.38***	50.63***	−65.51*
	(12.37)	(13.16)	(38.37)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1924	1924	1924
R-squared	0.234	0.082	.

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

Table A.6
Robustness check results – unemployment rate dependent variable

Variables	Model XIII: Broadband Availability	Model XIV: Wired Broadband Adoption	Model XV: Any Internet Adoption
bb_avail	−0.210***		
	(0.0468)		
bb_wired		−0.496***	
		(0.115)	
bb_any			−1.043***
			(0.303)
und_20	0.0185	−0.114*	−0.225**
	(0.0673)	(0.0651)	(0.107)
ov_64	−0.00667	−0.191***	−0.442***
	(0.0483)	(0.0589)	(0.134)
pctlesshs14to18	0.0312	−0.0970*	−0.349***
	(0.0444)	(0.0566)	(0.131)
pctcolgrad14to18	−0.0316	0.0962*	0.162*
	(0.0379)	(0.0543)	(0.0858)
pct_black	−0.0373*	−0.0765***	−0.0858**
	(0.0213)	(0.0267)	(0.0355)
pct_hispanic	0.0270	0.0444*	0.0187
	(0.0189)	(0.0227)	(0.0293)
pct_womanwchild	0.186***	−0.0125	−0.0771
	(0.0565)	(0.0731)	(0.103)
7.rucc_2013	−0.0198	0.378	0.0354
	(0.291)	(0.323)	(0.417)
8.rucc_2013	−1.121**	−0.665	−1.063
	(0.532)	(0.490)	(0.685)
9.rucc_2013	−0.628	0.0658	−0.464
	(0.439)	(0.430)	(0.571)
pcinc2018	−4.44e-06	5.31e-05**	8.54e-05*
	(1.71e-05)	(2.15e-05)	(4.59e-05)
gdp_growth	−0.00582*	−0.0101**	−0.0157***
	(0.00348)	(0.00421)	(0.00513)
pop_growth	0.00172	−0.0931*	−0.0303
	(0.0416)	(0.0537)	(0.0589)
popden	0.0439***	0.0345***	0.0595***
	(0.0115)	(0.0107)	(0.0186)
na_scale	−0.0667	−0.0594	0.0558
	(0.113)	(0.118)	(0.136)
dt100k	−0.00444**	0.00138	−0.00811**
	(0.00192)	(0.00228)	(0.00334)
tot_estabs	0.000169	0.000496	0.000378
	(0.000479)	(0.000539)	(0.000651)
min_wage	2.533***	5.719***	5.512***
	(0.852)	(1.188)	(1.409)
av_cases	−0.0740*	0.0300	0.123
	(0.0426)	(0.0500)	(0.0922)
always	0.00994	−0.0237	−0.0443*
	(0.0137)	(0.0167)	(0.0266)
Constant	−3.822	−12.10	51.88**
	(8.238)	(8.532)	(21.55)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.201	0.128	.

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

Table A.7
Robustness check results - pre-pandemic results (January and February 2020)

Variables	Model XVI	Model XVII	Model XVIII
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
bb_avail	0.361***		
	(0.0860)		
bb_wired		0.858***	
		(0.206)	
bb_any			1.812***
			(0.512)

(continued on next page)

Table A.7 (*continued*)

Variables	Model XVI	Model XVII	Model XVIII
	Broadband Availability	Wired Broadband Adoption	Any Internet Adoption
und_20	−0.0520	0.177	0.369**
	(0.126)	(0.127)	(0.181)
ov_64	−0.286***	0.0326	0.470**
	(0.104)	(0.126)	(0.238)
pctlesshs14to18	−0.250***	−0.0285	0.411*
	(0.0852)	(0.0944)	(0.218)
pctcolgrad14to18	0.151**	−0.0704	−0.186
	(0.0758)	(0.109)	(0.152)
pct_black	0.0553	0.123***	0.140**
	(0.0378)	(0.0460)	(0.0584)
pct_hispanic	0.0176	−0.0127	0.0315
	(0.0374)	(0.0403)	(0.0510)
pct_womanwchild	−0.221**	0.122	0.236
	(0.107)	(0.129)	(0.176)
7.rucc_2013	−0.519	−1.206**	−0.614
	(0.518)	(0.553)	(0.704)
8.rucc_2013	2.338**	1.559*	2.259*
	(0.962)	(0.909)	(1.202)
9.rucc_2013	0.990	−0.206	0.713
	(0.802)	(0.798)	(0.993)
pcinc2018	0.000183***	8.37e-05**	2.71e-05
	(5.21e-05)	(3.39e-05)	(5.62e-05)
gdp_growth	0.0205**	0.0280***	0.0376***
	(0.00875)	(0.00940)	(0.0127)
pop_growth	0.0702	0.234**	0.126
	(0.0805)	(0.100)	(0.101)
popden	−0.0680***	−0.0519***	−0.0957***
	(0.0220)	(0.0199)	(0.0323)
na_scale	0.0207	0.00962	−0.188
	(0.202)	(0.213)	(0.231)
dt100k	0.00689*	−0.00316	0.0133**
	(0.00391)	(0.00460)	(0.00597)
tot_estabs	0.000145	−0.000423	−0.000226
	(0.000853)	(0.000942)	(0.00116)
min_wage	−0.417	−5.926***	−5.599**
	(1.462)	(1.990)	(2.353)
av_cases	−0.0343	−0.214**	−0.377**
	(0.0809)	(0.0900)	(0.160)
always	0.0208	0.0789***	0.115**
	(0.0248)	(0.0294)	(0.0456)
Constant	35.49**	49.75***	−61.46*
	(14.73)	(14.22)	(36.61)
State Fixed Effects	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Observations	1625	1625	1625
R-squared	0.149	0.107	.

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

References

Alon, T., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). *The impact of COVID-19 on gender equality*. National Bureau of Economic Research Working Papers, No. w26947.

Amuedo-Dorantes, C., Marcén, M., Morales, M., & Sevilla, A. (2020). *COVID-19 school closures and parental labor supply in the United States*. IZA Discussion Papers, No. 13827.

Bick, A., Blandin, A., & Mertens, K. (2020). *Work from home after the COVID-19 outbreak*. Dallas, TX: Federal Reserve Bank of Dallas. Retrieved from the Federal Reserve Bank of Dallas: https://www.dallasfed.org/-/media/documents/research/papers/2020/wp2017.pdf.

BroadbandNow. (2021). *BroadbandNow estimates availability for all 50 states; confirms that more than 42 million Americans do not have access to broadband*. Retrieved from https://broadbandnow.com/research/fcc-broadband-overreporting-by-state.

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., & TuYe, H. Y. (2020). *COVID-19 and remote work: An early look at US data*. National Bureau of Economic Research Working Papers, No. w27344.

Bureau of Labor Statistics. (2020a). *The employment situation – february 2020* [Press Release] https://www.bls.gov/news.release/archives/empsit_03062020.pdf.

Bureau of Labor Statistics. (2020b). *The employment situation – April 2020* [Press Release] https://www.bls.gov/news.release/archives/empsit_05082020.pdf.

Bustillo, X. (2021). *Infrastructure bill passed: What's next for ag? Politico. 11/08/2021*. Available at: https://www.politico.com/newsletters/weekly-agriculture/2021/11/08/infrastructure-bill-passed-whats-next-for-ag-798728.

Congressional Research Service. (2021a). *Broadband data and mapping: Background and issues for the 117th congress*. Washington, DC: Congressional Research Service Report R45962. Retrieved from https://fas.org/sgp/crs/misc/R45962.pdf.

Congressional Research Service. (2021b). *Unemployment rates during the COVID-19 pandemic*. Washington, DC: Congressional Research Service Report R46554. Retrieved from https://fas.org/sgp/crs/misc/R46554.pdf.

Conroy, T., & Low, S. A. (2022). Entrepreneurship, broadband, and gender: Evidence from establishment births in rural America. *International Regional Science Review, 45*(1). https://doi.org/10.1177/01600176211018749

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal, 121*(552), 505–532.

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics, 189*, 104235. https://doi.org/10.1016/j.jpubeco.2020.104235

Federal Communications Commission. (2020). *2020 broadband deployment report*. Retrieved from https://docs.fcc.gov/public/attachments/FCC-20-50A1.pdf.

Gallardo, R., Whitacre, B., Kumar, I., & Upendram, S. (2021). Broadband metrics and job productivity: A look at county-level data. *The Annals of Regional Science, 66*(1), 161–184.

Grubesic, T. H. (2004). The geodemographic correlates of broadband access and availability in the United States. *Telematics and Informatics, 21*(4), 335–358.

Grubesic, T. H. (2012). The US national broadband map: Data limitations and implications. *Telecommunications Policy, 36*(2), 113–126.

Hasbi, M. (2017). Impact of very high-speed broadband on local economic growth: Empirical evidence. In *14th international telecommunications society Asia-Pacific regional conference: Mapping ICT into transformation for the next information society*.

Katz, R. L., & Berry, T. A. (2014). Strategies to promote broadband demand. In R. L. Katz, & T. A. Berry (Eds.), *Driving demand for broadband networks and services* (pp. 295–305). Springer International Publishing. https://doi.org/10.1007/978-3-319-07197-8_8.

Katz, R., & Jung, J. (2021). *The economic impact of broadband and digitization through the COVID-19 pandemic: Econometric modelling*. International Telecommunication Union, Development Sector. https://www.itu.int/pub/D-PREF-EF.COV_ECO_IMPACT_B-2021.

Katz, R., Jung, J., & Callorda, F. (2020). Can digitization mitigate the economic damage of a pandemic? Evidence from SARS. *Telecommunications Policy, 44*(10), 102044. https://doi.org/10.1016/j.telpol.2020.102044

Kim, Y., & Orazem, P. F. (2016). Broadband internet and new firm location decisions in rural areas. *American Journal of Agricultural Economics, 99*(1), 285–302.

Kolko, J. (2012). Broadband and local growth. *Journal of Urban Economics, 71*(1), 100–113.

Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. *Telecommunications Policy, 33*, 471–485.

Lattemann, C., Stieglitz, S., Kupke, S., & Schneider, A. (2009). Impact of PPPs to broadband diffusion in Europe. *Transforming Government: People, Process and Policy, 3*(4), 355–374.

Lee, H. J., & Whitacre, B. (2017). Estimating willingness-to-pay for broadband attributes among low-income consumers: Results from two FCC lifeline pilot projects. *Telecommunications Policy, 41*(9), 769–780.

Lehr, W. H., Osorio, C., Gillett, S. E., & Sirbu, M. A. (2006). *Measuring broadband's economic impact*. Retrieved from https://dspace.mit.edu/handle/1721.1/102779.

Leichtman Research Group. (2021). *About 4,860,000 added broadband from top providers in 2020* [Press Release]. Retrieved from https://www.leichtmanresearch.com/about-4860000-added-broadband-from-top-providers-in-2020/.

Lobo, B. J., Alam, M. R., & Whitacre, B. E. (2020). Broadband speed and unemployment rates: Data and measurement issues. *Telecommunications Policy, 44*(1), 101829.

Low, S. A. (2020). Rural development research and policy: Perspectives from federal and state experiences with an application to broadband. *The Review of Regional Studies, 50*(3), 311–322.

Low, S. A., Isley, C., Spell, A., Kures, M., Conroy, T., & Deller, S. (2021). *Broadband technologies: A primer on access and solutions* (DM601). University of Missouri Extension. Retrieved from. https://extension.missouri.edu/publications/dm601.

Mack, E. A. (2014). Businesses and the need for speed: The impact of broadband speed on business presence. *Telematics and Informatics, 31*(4), 617–627.

Mack, E. A. (2019). Geographic dimensions of broadband data uncertainty. *The Information Society, 35*(2), 95–106.

Mack, E. A., Anselin, L., & Grubesic, T. H. (2011). The importance of broadband provision to knowledge intensive firm location. *Regional Science Policy & Practice, 3*(1), 17–35.

Mack, E., & Faggian, A. (2013). Productivity and broadband: The human factor. *International Regional Science Review, 36*(3), 392–423.

Mora-Rivera, J., & García-Mora, F. (2021). Internet access and poverty reduction: Evidence from rural and urban Mexico. *Telecommunications Policy, 45*(2), 102076.

NCTA – The Internet and Television Association. (2021). *COVID-19: How cable's internet networks are performing – metrics, trends & observations*. Retrieved from https://www.ncta.com/COVIDdashboard.

OpenVault. (2021). *OpenVault broadband insights report (OVBI)*. Retrieved from https://openvault.com/wp-content/uploads/new/OpenVault_OVBI_Q420.pdf.

Pender, J. (2019). *Rural American at a glance* (2019 Edition). United States Department of Agriculture, Economic Research Service. Economic Information Bulletin 212. November. https://www.ers.usda.gov/publications/pub-details/?pubid=95340.

Prieger, J. E. (2003). The supply side of the digital divide: Is there equal availability in the broadband Internet access market? *Economic Inquiry, 41*(2), 346–363.

Rhinesmith, C., Reisdorf, B., & Bishop, M. (2019). The ability to pay for broadband. *Communication Research and Practice, 5*(2), 121–138.

Robbins, C. (2020). *Connected and secure: Webex in today's world*. Cisco. https://blogs.cisco.com/news/connected-and-secure-webex-in-todays-world.

Rosston, G. L., & Wallsten, S. J. (2020). Increasing low-income broadband adoption through private incentives. *Telecommunications Policy, 44*(9), 102020. https://doi.org/10.1016/j.telpol.2020.102020

Rostelecom. (2020). *Rostelecom networks robust enough to handle the extra demand for new connections and the increase in traffic during the Covid-19 lockdown* [Press Release]. Retrieved from https://www.company.rt.ru/en/ir/news_calendar/d454545/.

Schmit, T. M., & Severson, R. M. (2021). Exploring the feasibility of rural broadband cooperatives in the United States: The new New Deal? *Telecommunications Policy, 45*(4), 102114.

Spataro, J. (2020). *Update #2 on Microsoft cloud services continuity*. Microsoft https://www.microsoft.com/en-us/microsoft-365/blog/2020/03/29/update-2-microsoft-cloud-services-continuity/.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica: Journal of the Econometric Society*, 557–586.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg, 80*(4.2), 1.

United States Census Bureau. (2021). *1st quarter 2021 retail E-commerce sales report*. Retrieved from https://www.census.gov/retail/index.html#ecommerce.

2020 United States Department of Agriculture. (2020). *Rural-urban Continuum codes. Economic research service*. Retrieved from https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/.

United States Geological Survey. (2020). *National land cover Database*. Retrieved from https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php.

Wallsten, S. (2021). *KY, LA and some tribal areas lead early uptake of emergency broadband benefit program*. Technology Policy Institute blog post, July 15. Available at: https://techpolicyinstitute.org/publications/broadband/digital-divide/mapping-the-emergency-broadband-benefit-program/.

Warf, B. (2013). Contemporary digital divides in the United States. *Tijdschrift voor Economische en Sociale Geografie, 104*(1), 1–17. https://doi.org/10.1111/j.1467-9663.2012.00720.x

Whitacre, B., & Gallardo, R. (2020). State broadband policy: Impacts on availability. *Telecommunications Policy, 44*(9), 102025.

Whitacre, B., Gallardo, R., & Strover, S. (2014a). Broadband's contribution to economic growth in rural areas: Moving towards a causal relationship. *Telecommunications Policy, 38*(11), 1011–1023.

Whitacre, B., Gallardo, R., & Strover, S. (2014b). Does rural broadband impact jobs and income? Evidence from spatial and first-differenced regressions. *The Annals of Regional Science, 53*(3), 649–670.

Whitacre, B. E., & Mills, B. F. (2007). Infrastructure and the rural—urban divide in high-speed residential Internet access. *International Regional Science Review, 30*(3), 249–273.
Whitacre, B., & Rhinesmith, C. (2016). Broadband un-adopters. *Telecommunications Policy, 40*(1), 1–13. https://doi.org/10.1016/j.telpol.2015.11.008
White, M. C., & Spell, A. (2020). *Remote Work. COVID-19 Missouri Economy Indicator* (7th, Vol. 1). University of Missouri Extension. https://extension.missouri.edu/media/wysiwyg/Extensiondata/Pro/ExCEED/Docs/MissouriEconomy_COVID-19_015June2020.pdf.