Telework and COVID-19 Resiliency in the Southeastern United States

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Received: 10/17/2021
Accepted: 04/27/2022

Abstract

One potential driver of economic resiliency during the COVID-19 pandemic was the ability to telework. This paper estimates the factors influencing changes in unemployment rates for states in the Southeastern U.S. during two distinct periods: (1) the initial months of the pandemic, and (2) the recovery experienced from April through December 2020. Our results suggest industrial composition and demographic factors were strongly associated with the early rise in unemployment and the subsequent decline during the first nine months of the pandemic. The ability to telework was a crucial factor in changing unemployment levels, with local broadband adoption levels driving this relationship. Telework had a positive impact for counties with a high broadband adoption rate from February to April. However, counties with a high ability to telework, but low broadband adoption rates, were held back from recovering from April to December.

1 Introduction

Resilience is the ability for a local or regional population to withstand or recover from shocks to the economy Martin (2012). The resilience of communities was tested on a global scale in 2020, when the novel coronavirus (COVID-19) pandemic disrupted activity across the world, including in local communities, business and health care sectors, and national economies. Economic impacts resulted from local health mandates, public and private policy changes, and shifting behavior patterns in our professional and personal lives. Early in the pandemic, elected officials and employers prohibited non-essential public and private employees from gathering at work, leading many organizations to switch to working from home (telework) or to lay off workers to stop the spread of COVID-19. This dramatic shutdown led the U.S. economy into a brief – but deep – recession in March 2020 National Bureau of Economic Research (2020). At the start of 2020 the U.S. unemployment rate was 3.6%, and it rose to 14.7% in April U.S. Bureau of Labor Statistics (2020). Comparatively, peak unemployment during the 2007-2009 recession was 10.0% U.S. Bureau of Labor Statistics (2012). Although states initially began to reopen non-essential businesses towards the end of April, the rate of recovery was uneven across states and counties. By December the national unemployment rate had declined to 6.7% U.S. Bureau of Labor Statistics (2020).

These aggregate measures of unemployment do not tell the whole story, since COVID-19 related policies, cases, and economic shocks varied among states, counties, and cities. Of specific interest in this paper is the impact that the ability to telework had on unemployment trends in counties across the southeast after accounting for differences in disease prevalence, policies, and demographics. While telework has a relatively long history, it played a unique role in the COVID-19 pandemic – which changed the way we view the ability to work remotely.

This paper aims to improve the understanding of factors that impacted the rise and fall in county-level unemployment rates during the pandemic. Of particular interest is whether telework contributed to resilience and recovery in southeastern U.S. counties during the COVID-19 economic shock, as measured by the initial rise and subsequent recovery of unemployment rates. We hypothesize that counties with a high ability to work from home (which includes accounting for the local broadband situation) experienced greater resilience during the pandemic. Although seemingly crucial to the resilience of households and local economies, no published studies we are aware of have identified the impact of telework on unemployment changes during this pandemic or other periods. Further research on the challenges and opportunities the COVID-19 pandemic brought to the U.S. workforce is necessary to determine how employees, employers, and communities can recover and better prepare for future economic shocks.

2 Background

2.1 History of Telework

Teleworking began in the 1950s and was on the rise prior to the pandemic as advances in information and communication technologies allowed employees to complete their work anywhere at any time Joice (2000); Krantz-Kent (2019). Nilles (1975) coined the term "telecommuting" and predicted that it would become common due to factors such as urban sprawl, separation of business and residential areas, and dependence on transportation. These factors made decentralization appealing yet telework was slow to expand.

In 1996, people who teleworked made up 10% of the U.S. workforce Gibson et al. (2002). By 2017-2018, 42 million wage and salary workers (29% of the total workforce) had the ability to work from home – and 25.8% of them did U.S. Bureau of Labor Statistics (2020). This average hid significant heterogeneity by industry, however. For example, 57.4% of people working in finance, 53.4% of people working in professional and business services, and 53.3% of people working in information had the ability to work from home in 2017-2018 U.S. Bureau of Labor Statistics (2020). Alternatively, a much smaller percentage of job activities in hospitality, manufacturing, and construction are suited to telework Krantz-Kent (2019). Only 8.8% of people working in leisure and hospitality were positioned to work from home in 2017-2018 U.S. Bureau of Labor Statistics (2020).

2.2 Pandemic-era Employment

Research has found that telecommuting increases morale and productivity, provides flexibility, improves retention and recruitment opportunities, lowers costs, reduces absenteeism, and opens new labor pools; however, it diminishes communication and teamwork Gibson et al. (2002). During the COVID-19 pandemic, these benefits and drawbacks were likely even more apparent. The COVID-19 outbreak escalated to a global pandemic in March 2020 World Health Organization (2020). An executive order from President Donald Trump, and increasing confirmed cases in the U.S., led state governors and health officials to issue stay-at-home orders and temporarily close non-essential businesses. Federal and state guidance identified essential workers during the COVID-19 crisis that were not subject to stay-at-home orders and temporary closures. In some states, like Oklahoma, almost all industries were considered essential Oklahoma State Department of Health (2020), leaving local communities and businesses to make their own decisions about work situations. Industries identified as essential were allowed to have employees continue working at their traditional locations, with some health and safety modifications.

Table 1 shows when governors of the 12 southeastern states temporarily closed non-essential businesses, along with unemployment rates in February, April, and December 2020. Unemployment rates increased following the declaration of an emergency and closure of some businesses. Across the U.S., non-essential businesses began reopening in various capacities at the end of April and beginning of May. However, some states, counties, and cities adjusted their reopening plans continuously over the following months. For many

Americans in non-essential jobs, the COVID-19 suppression policies resulted in either working from home or being laid off.

Table 1: 2020 Non-essential business closures and unemployment rates by state in 2020

State	Date Closed	Feb. UNEMP	April UNEMP	Dec. UNEMP
Alabama	March 28th	2.60%	13.20%	4.70%
Arkansas	April 6th	3.80%	10.00%	4.90%
Florida	April 3rd	3.30%	14.00%	5.10%
Georgia	April 3rd	3.50%	12.50%	5.30%
Kentucky	March 26th	4.20%	16.90%	5.60%
Louisiana	March 23rd	5.20%	13.10%	7.90%
Mississippi	April 3rd	5.80%	15.70%	6.60%
North Carolina	March 30th	3.60%	13.50%	6.10%
Oklahoma	March 25th	3.10%	13.00%	4.50%
South Carolina	April 1st	2.80%	11.50%	5.60%
Tennessee	March 31st	3.90%	15.80%	5.60%
Texas	April 2nd	3.70%	12.90%	6.90%
Southeastern region		3.60%	13.40%	5.90%

Source: Governor's executive orders for each state and the Bureau of Labor Statistics

A study in May 2020 found that 90% of the initial wave of unemployment (Feb – March 2020) during COVID-19 was from jobs that could not be done remotely Kochhar and Passel (2020). Dingel and Neiman (2020) argue that during the initial phase of the pandemic nearly every worker who could shift to working from home did so. According to two surveys performed in April and May 2020, 35.2% of workers were commuting to work before COVID-19 but switched to teleworking as a response, 15% of workers were already working from home prior to COVID, and 10.1% of people surveyed were laid off or furloughed since March 2020 Brynjolfsson et al. (2020). This data implies that about half of the workforce worked from home during the initial phase of the pandemic. Jobs that primarily use the Internet, telephone, and email to complete tasks were likely easier to perform remotely than those requiring in-person services Messenger (2017). Thus, a greater number of workers in management, professional, and related occupations had an easier transition to remote work compared to employees in other industries.

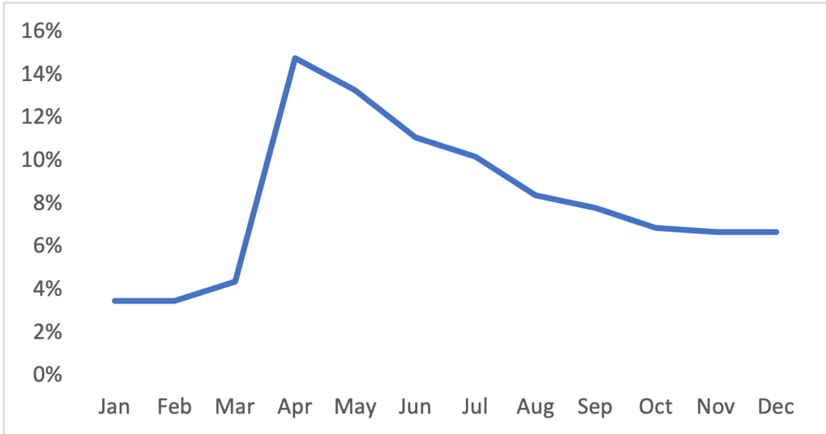
Federal policy interventions to counter COVID-19 impacts occurred in a multi-step process. One of the most critical pieces of legislation for businesses was the Coronavirus Aid, Relief, and Economic Security (CARES) Act in March 2020. The CARES Act authorized new programs and appropriated funds to expand existing programs to provide fast and direct assistance for American workers, families, and small businesses, and to preserve jobs US Department of Treasury (2020). These programs included expanded unemployment benefits and the Payroll Protection Program (PPP). The PPP provided small businesses with funds to maintain payroll, including benefits, and to cover overhead US Department of Treasury (2020). As of August 8, 2020, more than 5.2 million loans were approved totaling over $525 billion in awards U.S. Small Business Administration (2020). Early work suggests counties with more PPP loans experienced lower unemployment rates during the initial phase of the pandemic Barraza et al. (2020).

Figure 1 illustrates the monthly U.S. unemployment rate throughout 2020. Most states followed a similar pattern of unemployment rates peaking in April and slowly tapering off throughout the rest of the year. Figure 2 demonstrates that unemployment rates were dramatically different across industry sectors during this time, with industries such as leisure/hospitality and other services experiencing significantly higher rates than agriculture/financial activities. It is worth noting that most of the industries that comprise a higher proportion of the workforce in rural areas (such as healthcare, agriculture, or manufacturing) were deemed essential during the pandemic. As a result, these sectors saw relatively muted shifts in unemployment rates.

Differences in pandemic impacts across the rural-urban [1] spectrum can also be attributed to COVID-19

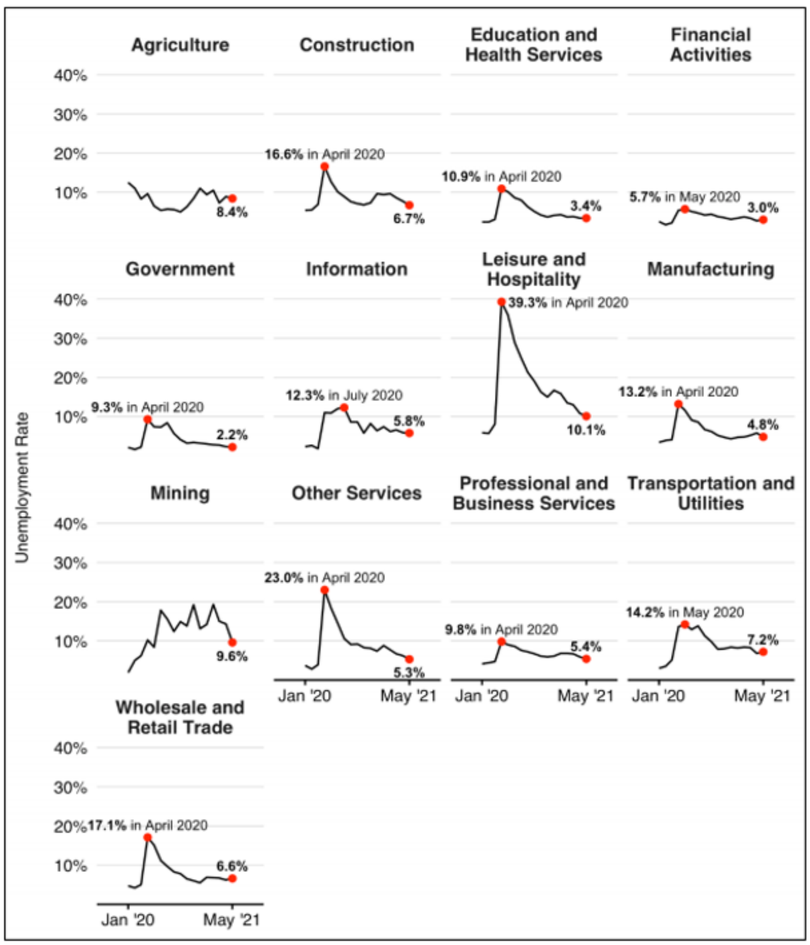
[1] The Census Bureau defines rural as all areas not in an urban area (typically 2,500 population). Nonmetropolitan is a

Figure 1: National unemployment trends, Jan – Dec 2020



Source: Bureau of Labor Statistics, 2020

Figure 2: Unemployment rates by sector, Jan – May 2020



Source: Congressional Research Service, 2021

county-level classification based on population and proximity to a metro area. However, the terms rural and non-metropolitan are used interchangeably in this paper.

prevalence and population density USDA Economic Research Service (2021). The pandemic started out more prevalent in urban areas and then worked its way into rural communities, which experienced higher case rates per capita in late 2020 and 2021. Rural areas have lower median household income, higher poverty, and are not as efficient in providing and administering public goods Kilkenny (2010). Fewer resources likely made the rippling effects of the pandemic more prominent in rural areas. This includes the availability of rural healthcare facilities – particularly hospitals suited to deal with COVID-19 cases.

2.3 Importance of Broadband

An important consideration in the discussion around telework is the local broadband situation. Although some jobs may be considered telework-friendly, employees may not have Internet or computer access at home – prohibiting them from doing so. Seven percent of households in the U.S. did not have a computer and 13% did not have an Internet subscription as of 2019 Martin et al. (2021). Gallardo and Whitacre (2018) highlight the importance of broadband speeds and adoption in telework viability. In nonmetro counties high broadband adoption rates are associated with lower unemployment growth, and a similar finding holds for overall productivity Whitacre et al. (2014); Gallardo et al. (2021). However, rural broadband access lagged even prior to COVID-19 Whitacre (2021), and the lack of reliable broadband connectivity is a consideration for effective telework.

A recent study found broadband availability and wired broadband adoption to have a significant impact on rural employment throughout the pandemic Isley and Low (2022). However, this study focuses on the impact of broadband at specific points in time. Notably, they find a similar impact of broadband on employment for both the pre (Jan – Feb) and post (Apr – May) breakout period. The authors issue a call for additional work that focuses explicitly on changes in employment rates. Our study answers this call. While our focus is on the role of broadband in the ability to telework, broadband may have impacted telemedicine adoption as well as remote learning for rural students during the pandemic. These challenges put nonmetro areas at an additional disadvantage.

3 Materials and Methods

3.1 Data

This paper estimates the factors influencing changes in unemployment rates for counties in the 12 southeastern region states during two distinct phases of the COVID-19 pandemic: (1) the initial increase in unemployment observed between February and April 2020, and (2) the decline in unemployment between May and December 2020. We combine pre-pandemic data on the industry composition of a county (at the 2-digit NAICS level) [2] with the O*NET-derived baseline of how many jobs can be performed from home Dingel and Neiman (2020), and control for other factors that likely influenced unemployment rates such as dependence on individual industries and local education, age, and racial characteristics. We also control for factors specific to the challenges of the pandemic such as the number of COVID cases, federal Paycheck Protection Program (PPP) loans, and broadband. Additionally, we control for initial unemployment levels in the two phases (February and April, respectively) since these baseline rates likely affect the resulting shifts.

We control for the percentage of county employment in the agriculture, manufacturing, construction, wholesale/retail trade, leisure/hospitality, government, transportation, information, education, and business industry sectors in the model. The employment by industry in each county as of 2019 is available from Emsi, a labor market data company. Although some industries may have been hit particularly hard during the pandemic due to shutdown orders, we control for all industries in our model to determine the positive or negative impact of each USDA Economic Research Service (2021); Klein and Smith (2021).

The telework variable was created using the number of people employed in each county by industry from 2019 BLS data. We combine that number with the O*NET derived baseline of the share of jobs that can be

[2] North American Industrial Classification System, used by the U.S. Bureau of Labor Statistics

Table 2: Share of jobs that can be done at home, by industry

Occupation	O*NET-derived baseline of jobs that can be performed remotely
Computer and mathematical	1.00
Education, training, and library	0.98
Legal	0.97
Business and Financial Operations	0.88
Management	0.87
Arts, design, entertainment, sports, and media	0.76
Office and admin support	0.65
Architecture and engineering	0.61
Life, physical, and social science	0.54
Community and social service	0.37
Sales and related	0.28
Personal care and service	0.28
Protective service	0.06
Healthcare practitioners and technical	0.05
Transportation and material moving	0.03
Healthcare support	0.02
Farming, fishing, and forestry	0.01
Production	0.01
Installation, maintenance, and repair	0.01
Construction and extraction	0.00
Food preparation and serving related	0.00
Building and grounds cleaning and maintenance	0.00

Source: Dingel and Neiman, 2020.

done from home by industry from Dingel and Neiman (2020). These are national estimates on the percentage of jobs that can be done remotely by major industry group, calculated by merging responses to the Work Context Questionnaire and Generalized Work Activities Questionnaire available from O*NET with BLS data on industry employment Dingel and Neiman (2020). For each county, we multiplied the number of workers in each industry by the respective estimate of the percent of jobs that could be performed remotely (Table 2). We then summed these estimates across industries in the county and divided by total employment in these industries, giving us an estimate of the percent of workers with the ability to telework. The variation in a county's ability to telework using this methodology can be seen in Figure 3.

The broadband variable included in our model is a measure from the American Community Survey on the percentage of households with a broadband subscription of any type. This measure of broadband includes households with Satellite Internet service; cable, fiber optic or DSL; or a cellular data plan. However, a limitation of this broadband measure is that individuals may not possess a broadband speed sufficient for remote work.

Summary statistics and data sources for the variables in the analysis are displayed in Table 3. The telework variable has an average of 0.30 (relatively consistent with Dingel and Neiman) and ranges from 0.22 to 0.43 – indicating that the possibility of teleworking varied significantly among the counties in the study region. We include measures of the percentage of county households that have a broadband subscription from the 2015-2019 American Community Survey, since Internet connection is important for participating in telework. A metro dummy variable, determined based on Rural-Urban Continuum Codes (RUCCs), is also included, since proximity to a metropolitan area could influence how unemployment rates change. There are 1,206 counties in the southeastern region: 468 metro and 738 nonmetro.

3.2 Model Specification

The factors driving the change in unemployment during the pandemic were first estimated via Ordinary Least Squares (OLS) regression analysis for the two phases of the outbreak in 2020. For the first phase between February and April, possible explanatory variables included COVID-19 cases in April, PPP loans made in April, February unemployment rates, and independent variables listed in Table 3. For the second phase

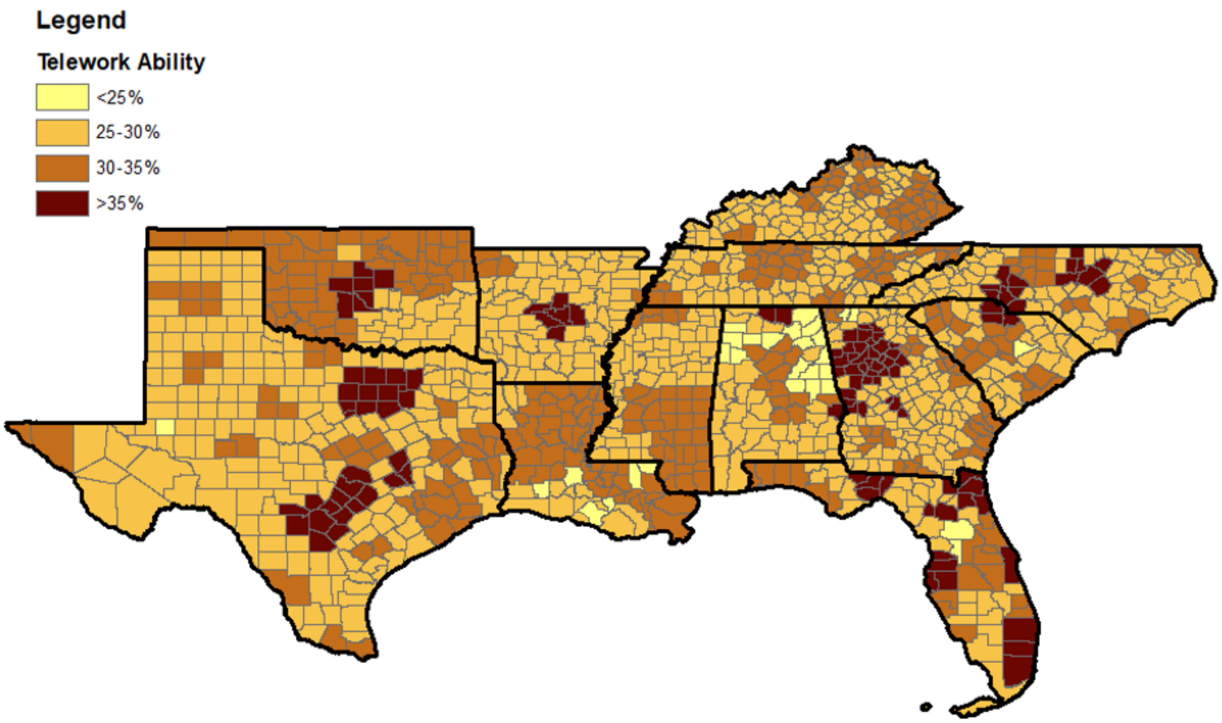
Table 3: Summary statistics

Dependent Variables		Type	Data Source (Year)	Mean (Std. Dev.)	(Min, Max)
UNEMPFebApril	Change in unemployment from February to April	%	BLS (2020)	0.078 (0.039)	(-0.015, 0.266)
UNEMPAprilDec	Change in unemployment from April to December	%	BLS (2020)	0.061 (0.041)	(-0.017, 0.259)
Independent Variables Feb to April					
FebUNEMP	February unemployment rate	%	BLS (2020)	0.042 (0.016)	(0.012, 0.161)
AprilCOVID	Cumulative COVID cases per capita as of April 30th	Ratio	USA Facts (2020)	0.027 (0.048)	(0, 0.583)
lnAprilPPP	Natural log of PPP loans received per capita from 4/3 – 4/21	Ratio	SBA (2020)	6.326 (0.712)	(-0.422, 7.935)
Independent Variables April to Dec					
AprilUNEMP	April unemployment rate	%	BLS (2020)	0.120 (0.042)	(0.020, 0.317)
MayDecCOVID	Cumulative COVID cases per capita as of December 31st	Ratio	USA Facts (2020)	5.690 (2.834)	(0.459, 39.476)
lnMayDecPPP	Natural log of PPP loans received per capita from 4/22 – 8/8	Ratio	SBA (2020)	5.444 (1.159)	(-0.940, 13.663)
Independent Variables All Regressions					
TeleworkAbility	Percent of people able to telework across all industry sectors	%	BLS (2019) and Dingel and Neiman (2020)	0.301 (0.036)	(0.220, 0.433)
Broadband	Percent of households with a broadband subscription	%	ACS (2019)	0.714 (0.096)	(0.348, 0.938)
Agriculture	Percent of total employment in agriculture, forestry, finishing, hunting, and mining	%	Emsi (2019)	0.104 (0.088)	(0.001, 0.450)
Manufacturing	Percent of total employment in manufacturing	%	Emsi (2019)	0.090 (0.075)	(0, 0.667)
Construction	Percent of total employment construction	%	Emsi (2019)	0.065 (0.033)	(0.005, 0.592)
Trade	Percent of total employment in retail and wholesale trade	%	Emsi (2019)	0.124 (0.028)	(0.010, 0.235)
LeisureHospitality	Percent of total employment in arts, entertainment, leisure, and hospitality	%	Emsi (2019)	0.074 (0.031)	(0.007, 0.448)
Government	Percent of total employment in public administration and government	%	Emsi (2019)	0.206 (0.066)	(0.045, 0.881)
Transportation	Percent of total employment in transportation, warehousing, and utilities	%	Emsi (2019)	0.051 (0.030)	(0.005, 0.336)
Information	Percent of employment in information, finance, insurance, real estate, rental, and leasing	%	Emsi (2019)	0.079 (0.035)	(0.010, 0.473)
Education	Percent of employment in educational services, and health care and social assistance	%	Emsi (2019)	0.100 (0.045)	(0.008, 0.284)
Business	Percent of employment in professional, scientific, management, administrative, and waste management services	%	Emsi (2019)	0.041 (0.023)	(0.005, 0.283)
Metro	Counties with a Rural Urban Continuum Code from 1 to 3	Dummy	ERS (2013)	0.388 (0.488)	(0, 1)
lnMedEarn	Natural log of median earnings of the population over 16	Continuous	ACS (2019)	10.282 (0.155)	(9.561, 10.940)
CollegePlus	Percent of the population over 25 years with a bachelor's degree or higher	%	ACS (2019)	0.188 (0.081)	(0, 0.598)
Under18	Percent of the population under 18	%	ACS (2019)	0.226 (0.032)	(0.073, 0.360)
Over65	Percent of the population over 65	%	ACS (2019)	0.181 (0.045)	(0.032, 0.567)
Female	Percent of the population who is female	%	ACS (2019)	0.501 (0.028)	(0.335, 0.560)
Black	Percent of the population who is black	%	ACS (2019)	0.171 (0.184)	(0, 0.872)
Hispanic	Percent of the population who is Hispanic	%	ACS (2019)	0.119 (0.170)	(0, 0.992)
MultiRace	Percent of the population who identifies as multiple races	%	ACS (2019)	0.019 (0.019)	(0, 0.162)

BLS: Bureau of Labor Statistics; SBA: Small Business Administration; ACS: American Community Survey; ERS: Economic Research Service

Loveland County, Texas, had a missing observation for median income and was estimated using other Census data.

Figure 3: Percent of county employees able to telework



Source: Dingel and Neiman (2020), Emsi, and author's calculations

between April and December, possible explanatory variables included PPP loans from May to December, April unemployment, and independent variables in Table 3. The models were run for all 1,206 counties in aggregate. Our specification takes the form:

$$\Delta y_i = \alpha + \gamma \mathbf{X}_i + \beta_1 Telework_i + \beta_2 Broadband_i + \beta_3 Telework_i \times Broadband_i + \varepsilon_i \tag{1}$$

where y represents unemployment rates for the months of interest. The change in y is between two specific months of interest: pre-pandemic to peak unemployment (Feb to April), and peak unemployment to year-end (April to Dec). On the right-hand side, X is a vector of control variables not related to teleworking, Telework and Broadband are rates of telework ability and local household broadband adoption rates, and ε is an error term, all for county i.

In addition, a spatial lag model was employed as a robustness check and to account for unemployment rates being influenced by those of surrounding counties. This takes the form:

$$\Delta y_i = \rho W \Delta y_i + \gamma \mathbf{X}_i + \beta_1 Telework_i + \beta_2 Broadband_i + \beta_3 Telework_i \times Broadband_i + \varepsilon_i \tag{2}$$

where W is a queen-contiguity weight matrix and the parameter ρ captures spillovers in local demand shocks from neighboring counties, which have been demonstrated in the literature Molho (1995); Cracolici et al. (2009).

In the first phase of the pandemic analyzed, we define the dependent variable as the change in unemployment rates between February and April 2020 (i.e. unemp(Apr) – unemp(Feb)). Here a positive number represents higher unemployment rates in April, and so a positive ρ or β coefficient represents a factor that is associated with an increase in unemployment (i.e., less resilience). In the second phase of the pandemic in 2020, we create the dependent variable by subtracting December unemployment from the higher April rates (i.e. unemp(Apr) – unemp(Dec)). Thus, a positive ρ or β coefficient represents a factor associated with a larger recovery – which could be interpreted as being more resilient or more fully recovering to lower unemployment levels. Each specification includes an interaction term between the telework variable and the percentage of households with a broadband subscription because the ability to telework may be tempered by low broadband adoption rates – or boosted by high ones. Assessing the impact of telework on changes in unemployment requires also considering the interaction term coefficient (β_3).

4 Results and Discussion

4.1 The Rise in Unemployment from February to April

Table 4 illustrates the results of the initial specification exploring the rise in unemployment during the first two months of the pandemic. The parameter estimates are reported for the OLS model and the marginal effects are reported for the spatial lag model. The spatial lag model parameter estimates must be interpreted using marginal effects that indicate how each independent variable effects the expected outcome of the dependent variable LeSage and Pace (2014). The direct effect represents the effect of the change within the county, the indirect effect is the spillover effect from other counties, and the total effect is the sum of the direct and indirect effects StataCorp (2017).

Since the parameter estimates from the spatial lag model are not readily interpretable, we will only present the marginal effects. However, the results for both models are largely similar. Significant OLS parameter estimates are slightly reduced in the spatial lag model. This indicates that ignoring the spatial pattern of unemployment rates is omitting an important variable. Additionally, the ρ (rho) parameter estimate is also highly significant ($\rho = 0.414$, p<0.01) providing more evidence the spatial model is a better fit. The Moran's I value of the residuals was sizeable and highly significant for OLS (I = 0.434, p<0.01) but not significant for the spatial lag (I = -0.009, p=0.34) affirming the spatial model took care of relevant spatial patterns and suggests state-level controls are not needed. Consequently, we will discuss the spatial lag model total effects here. The combination of independent variables accounted for 35.4% of the variability in the rise in unemployment from February to April 2020 as measured by the unadjusted R-squared.

Factors that most significantly decrease the rise in unemployment were the percentage of the county population that: had a college education; were under 18 or over 65; or were black. Conversely, factors that were most significantly associated with a further increase in the rise in unemployment were the February unemployment rate, metropolitan status, median earnings, and the percentage of the county population that were: female; Hispanic; multiracial; or employed in leisure and hospitality, information, or manufacturing. Neither the OLS nor spatial lag models allow for causality to be determined. A significant coefficient does not mean that variable causes unemployment rates to change, but merely denotes an association between the two.

Our main relationship of interest is between telework and the change in unemployment. Here, none of our marginal effects are statistically significant: telework (p=0.50), broadband (p=0.46), or the interaction term (p = 0.98). However, assessing the marginal effects at specific fixed broadband levels could result in statistically significant relationships even though the component and interaction terms lack significance.[3] The modeling specification requires us to assess the coefficients of the telework and the $telework \times broadband$ variables simultaneously. We do this by calculating marginal effects at fixed broadband subscription levels (Figure 4, Table 5).[4] Broadband subscription rates range from 0.34 to 0.94 across the counties in our sample (Table 3), and the results demonstrate that these differences are vital. The ability to telework had no impact on unemployment rates from February to April in counties with broadband adoption rates under

[3]This is because the relevant variance and covariance matrices shift across levels of broadband adoption. The delta method (implemented via the MARGINS command in Stata) for evaluating the interaction would use $g(b) = \beta_{Telework} + \beta_{Telework \times Broadband} \times Broadband$. Then $\partial g(b)/\partial \beta_{Telework} = 1$, and $\partial g(b)/\partial \beta_{Telework \times Broadband} = Broadband$. The vector for dg/db is then [1 Broadband], and the resulting $var(g(b)) = dg'/dbcov(b)dg/db''$. Thus, the $var(g(b))$ can increase or decrease depending on the value of broadband and $cov(b)$. We thank Dr. Dayton Lambert for his help with this interpretation.

[4]Importantly, the marginal effects for the spatial lag model also include evaluating the spatially lagged dependent variable and are not as simple to calculate as for the OLS model, where they can be reconstructed solely using $\beta_{Telework}$ and $\beta_{Telework \times Broadband}$.

Table 4: Change in unemployment from February to April regression results

Variable	**OLS**		**Spatial Lag Model**					
	Parameter Estimate	**p-value**	**Direct Effect**	**p-value**	**Indirect Effect**	**p-value**	**Total Effect**	**p-value**
Telework	-0.207	0.386	-0.136	0.502	-0.075	0.503	-0.211	0.502
Broadband	0.047	0.611	0.058	0.464	0.032	0.467	0.090	0.464
Telework*Broadband	0.029	0.925	-0.005	0.984	-0.003	0.984	-0.008	0.984
AprilCOVID	0.025	0.224	0.026	0.018	0.014	0.157	0.041	0.150
lnAprilPPP	**-0.002**	**0.100**	-0.001	0.386	-0.001	0.385	-0.002	0.385
FebUNEMP	**0.514**	**0.000**	**0.460**	**0.000**	**0.252**	**0.000**	**0.712**	**0.000**
Agriculture	-0.031	0.556	-0.012	0.808	-0.007	0.808	-0.019	0.808
Manufacturing	**0.109**	**0.041**	**0.093**	**0.051**	**0.051**	**0.058**	**0.143**	**0.052**
Construction	0.021	0.740	0.003	0.963	0.001	0.963	0.004	0.963
Trade	-0.045	0.492	-0.041	0.514	-0.023	0.516	-0.064	0.514
LeisureHospitality	**0.374**	**0.000**	**0.371**	**0.000**	**0.203**	**0.000**	**0.574**	**0.000**
Government	0.004	0.936	0.018	0.715	0.010	0.715	0.028	0.715
Transportation	0.014	0.793	0.024	0.657	0.013	0.658	0.038	0.658
Information	0.083	0.177	**0.103**	**0.057**	**0.057**	**0.068**	**0.160**	**0.059**
Education	0.039	0.481	0.043	0.407	0.024	0.410	0.067	0.408
Business	-0.016	0.818	-0.073	0.264	-0.040	0.275	-0.113	0.267
Metro	**0.012**	**0.000**	**0.010**	**0.000**	**0.006**	**0.000**	**0.016**	**0.000**
lnMedEarn	**0.016**	**0.066**	**0.016**	**0.038**	**0.009**	**0.046**	**0.025**	**0.039**
CollegePlus	**-0.061**	**0.002**	**-0.059**	**0.002**	**-0.032**	**0.004**	**-0.091**	**0.002**
Under18	**-0.308**	**0.000**	**-0.242**	**0.000**	**-0.133**	**0.000**	**-0.375**	**0.000**
Over65	**-0.272**	**0.000**	**-0.197**	**0.000**	**-0.108**	**0.000**	**-0.305**	**0.000**
Female	**0.346**	**0.000**	**0.271**	**0.000**	**0.149**	**0.000**	**0.420**	**0.000**
Black	**-0.044**	**0.000**	**-0.028**	**0.000**	**-0.015**	**0.000**	**-0.043**	**0.000**
Hispanic	0.003	0.691	**0.014**	**0.037**	**0.008**	**0.054**	**0.022**	**0.041**
MultiRace	**0.129**	**0.013**	**0.129**	**0.008**	**0.071**	**0.013**	**0.199**	**0.009**
Constant	-0.155	0.248						
Number of Obs.	1,206		1,206					
R2	0.36		0.354					

Note: the coefficients for log variables must be transformed before interpreting by raising the natural number, e, to the power of the parameter estimate.
A negative sign indicates a smaller increase in unemployment, thus more resilience.
The values shown for the spatial lag model are marginal effects, not coefficients.

50%. Although some individuals may have been employed in occupations that were telework-friendly, their home broadband situation may have prevented them from continuing work. Alternatively, telework increased resilience in counties with higher broadband adoption rates, with marginal effects of -0.21 percentage points.

The February unemployment rate was found to significantly increase the rise in unemployment, signaling that the rise in unemployment was higher for counties already experiencing unemployment challenges. Although marginal effects cannot be determined for the spatially lagged dependent variable, it was significant in the regression. This indicates neighboring counties' rising unemployment rates impacted their own.

As hypothesized, industry composition was an important determinant of the rise in unemployment during the early months of the pandemic. A one percentage point increase in the percentage of employment in the manufacturing, leisure/hospitality, and information industry sectors were associated with average increases in unemployment rates by 0.143, 0.574 and 0.160 percentage points, respectively. The manufacturing and leisure/hospitality industries were likely impacted by social distancing requirements, the closure of non-essential businesses, and stay-at-home orders. The information industry sector contributing to a greater rise in unemployment is less intuitive but may be connected to initial business uncertainty when the pandemic hit even though this is an industry with more flexible telework ability.

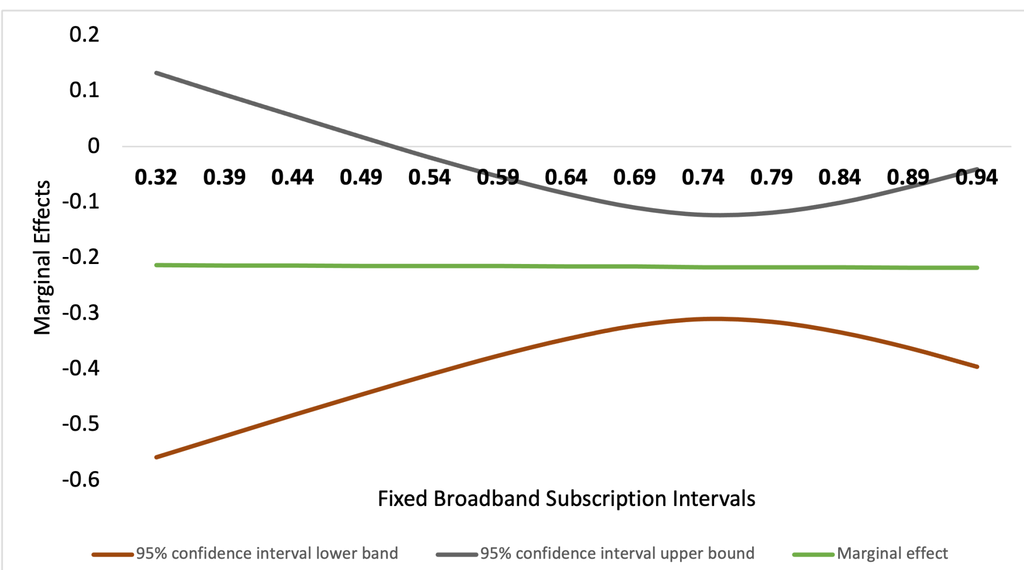
Metropolitan counties were associated with higher rises in unemployment during the initial stage of the pandemic. This could be the result of the coronavirus spreading in metro counties initially and being slower to spread to nonmetro areas. Likewise, higher median earnings was also associated with larger increases in unemployment. This may be due to greater difficulty in paying higher-wage employees when business has declined or remains uncertain.

Two characteristics with relatively large negative associations with increasing unemployment (i.e., led to greater resilience) were the percentages of the population under 18 and over 65. This was expected, as these populations are less likely to be in the workforce. Additionally, a one percentage point increase in the percent

Table 5: Marginal effect of telework on the change in unemployment from February to April and April to December 2020 at fixed broadband subscription levels

	February to April 2020		April to December 2020	
Broadband Adoption Level	Marginal Effect	p-value	Marginal Effect	p-value
0.34	-0.213	0.227	-0.219	0
0.39	-0.214	0.173	-0.198	0
0.44	-0.214	0.119	-0.176	0
0.49	-0.215	0.069	-0.154	0
0.54	-0.215	0.031	-0.132	0
0.59	-0.215	0.009	-0.11	0
0.64	-0.216	0.001	-0.089	0
0.69	-0.216	0	-0.067	0
0.74	-0.217	0	-0.045	0.007
0.79	-0.217	0	-0.023	0.186
0.84	-0.217	0	-0.002	0.942
0.89	-0.218	0.003	0.02	0.437
0.94	-0.218	0.016	0.042	0.189

Figure 4: Impact of telework on the change in unemployment from February to April 2020 at fixed broadband subscription levels



of the college-educated population is associated with a decrease in the rise in unemployment from February to April by 0.091 percentage points. This could be due to these populations being more likely to work in jobs that were able to transition to remote positions during the pandemic. A one percentage point increase in females is associated with a 0.420 percentage point increase in unemployment. This is consistent with prior research that the COVID-19 recession was more challenging for women in the workforce Karageorge (2020). Remote schooling of children under 18 likely impacted women with school-age children at home. However, we note that if females dropped out of the labor force due to these challenges, they would not be counted in the unemployment rate.

We controlled for race and ethnicities in our model due to their established correlation with unemployment rates in the literature. We found that counties with a greater percentage of individuals who identify as Hispanic or multiracial experienced a greater increase in unemployment rates, while counties with a greater percentage of people identifying as Black experienced a decrease in unemployment. Minorities regularly experience higher unemployment rates. The smaller increase in the rise in unemployment for counties with a larger percentage of Black individuals may have been related to industry composition.

4.2 The Change in Unemployment from April to December

After the peak of unemployment in April 2020, almost all counties in the southeast region experienced a decline in unemployment by December. Table 6 showcases the parameter estimates of the OLS model and the marginal effects of the spatial lag model. The combination of independent variables in the spatial lag regression accounted for 88.2% of the variability of the change in unemployment from April to December – significantly better than the 35% for the earlier period model. The results generally indicate that several of the same factors contributing to a lower increase in unemployment from February to April also contributed to a greater reduction in unemployment from April to December. One consideration when interpreting the effects from April to December is that counties with a smaller initial increase in unemployment as of April naturally had a smaller gap to recovery by December, so the question of resilience and recovery requires closer examination. Here recovery is being measured as the extent to which unemployment was reduced between April and December.

Our primary interest remains considering the relationship between telework and unemployment levels. During the April to December period, areas where a high percentage of workers could telework – but had low broadband adoption – saw lower rates of recovery (Figure 55, Table 5). Although during the initial months of the pandemic a high ability to telework and a high broadband adoption rate had a positive impact on unemployment rates, the longer-term effects were more diminished. Although telework may have helped reduce unemployment at the start of the pandemic, local broadband adoption rates had to be high enough to take advantage of the situation (Figure 4). This is a striking finding that local broadband adoption rates are crucial for the potential impact of telework.

During this later period, PPP loans appear to be effective at reducing unemployment rates. This may be an issue of timing—many PPP loans were issued in the summer of 2020. More COVID cases per capita are also associated with a higher recovery, perhaps because the second wave of the pandemic peaked around the end of 2020, but few states re-enacted official shutdowns. However, this could also be due to reverse causality where more people returned to in-person work, leading to a faster decline in unemployment rates, but also an increase in COVID cases.

Higher levels of employment in the construction, education, and business industries were associated with a smaller decline in unemployment. Strikingly, none of the industries controlled for here appear to contribute to a faster recovery through December relative to the ‘other’ category of industries in the intercept term. Metro areas experienced a greater decline in unemployment during this period. Baseline unemployment levels again prove to be important since counties with higher rates in April had more room to decline. A one percent higher April unemployment rate is associated with a 0.833 percentage point reduction in the unemployment gap between then and December.

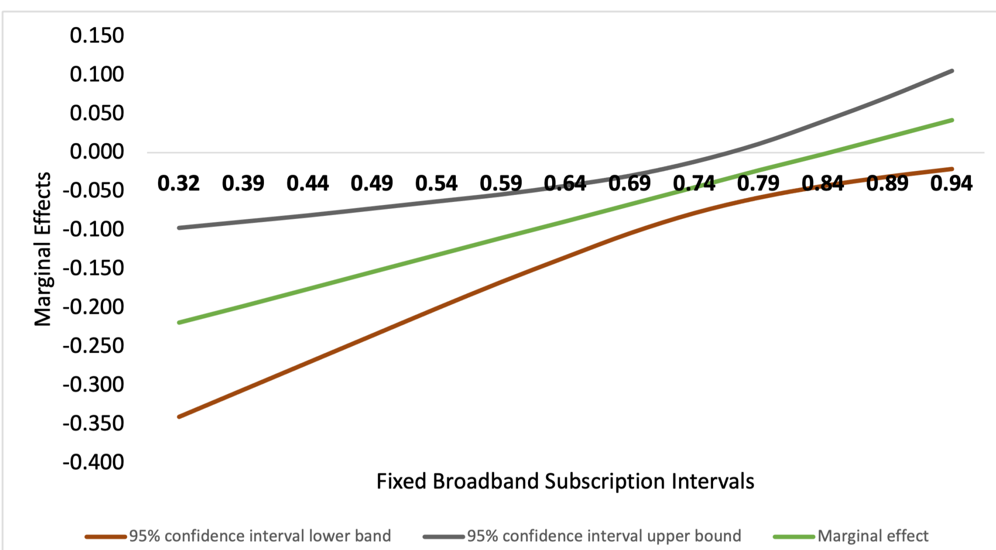
Although we cannot interpret spatial lag coefficients using marginal effects (since they are rolled into the indirect component), the positive and significant ρ coefficient ($\rho = 0.151$, $p<0.01$) indicates that neighboring county recovery rates were important for recovery, but that the association was dramatically lower than in

Table 6: Change in unemployment from April to December regression results

Variable	OLS		Spatial Lag Model					
	Parameter Estimate	**p-value**	**Direct Effect**	**p-value**	**Indirect Effect**	**p-value**	**Total Effect**	**p-value**
Telework	**-0.370**	**0.000**	**-0.319**	**0.001**	**-0.048**	**0.002**	**-0.367**	**0.001**
Broadband	**-0.110**	**0.006**	**-0.090**	**0.018**	**-0.014**	**0.022**	**-0.103**	**0.017**
Telework*Broadband	**0.440**	**0.001**	**0.379**	**0.003**	**0.057**	**0.005**	**0.436**	**0.003**
MayDecCOVID	**0.001**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**
lnMayDecPPP	**0.001**	**0.002**	**0.001**	**0.001**	**0.000**	**0.002**	**0.001**	**0.001**
AprilUNEMP	**0.781**	**0.000**	**0.724**	**0.000**	**0.109**	**0.000**	**0.833**	**0.000**
Agriculture	-0.026	0.299	-0.022	0.347	-0.003	0.350	-0.026	0.347
Manufacturing	0.008	0.720	0.005	0.809	0.001	0.809	0.006	0.809
Construction	**-0.064**	**0.020**	**-0.064**	**0.018**	**-0.010**	**0.025**	**-0.074**	**0.018**
Trade	-0.038	0.202	-0.039	0.183	-0.006	0.191	-0.045	0.183
LeisureHospitality	0.011	0.730	0.029	0.295	0.004	0.306	0.034	0.296
Government	-0.032	0.188	-0.029	0.228	-0.004	0.233	-0.033	0.227
Transportation	-0.040	0.134	-0.036	0.164	-0.005	0.171	-0.042	0.164
Information	-0.046	0.116	-0.035	0.168	-0.005	0.172	-0.041	0.168
Education	**-0.056**	**0.032**	**-0.053**	**0.033**	**-0.008**	**0.040**	**-0.061**	**0.033**
Business	-0.041	0.206	**-0.058**	**0.062**	**-0.009**	**0.076**	**-0.066**	**0.063**
Metro	**0.005**	**0.000**	**0.005**	**0.000**	**0.001**	**0.000**	**0.006**	**0.000**
lnMedEarn	0.004	0.292	0.006	0.106	0.001	0.119	0.006	0.106
CollegePlus	**0.030**	**0.002**	**0.026**	**0.003**	**0.004**	**0.006**	**0.030**	**0.003**
Under18	**-0.072**	**0.004**	**-0.059**	**0.010**	**-0.009**	**0.013**	**-0.068**	**0.010**
Over65	-0.022	0.182	-0.011	0.494	-0.002	0.492	-0.012	0.493
Female	0.035	0.161	0.024	0.263	0.004	0.264	0.028	0.263
Black	**-0.055**	**0.000**	**-0.047**	**0.000**	**-0.007**	**0.000**	**-0.054**	**0.000**
Hispanic	**-0.045**	**0.000**	**-0.036**	**0.000**	**-0.005**	**0.000**	**-0.041**	**0.000**
MultiRace	**0.045**	**0.015**	**0.048**	**0.033**	**0.007**	**0.043**	**0.055**	**0.034**
Constant	0.043	0.489						
Number of Obs.	1,206		1,206					
R2	0.881		0.882					

Note: the coefficients for log variables must be transformed before interpreting by raising the natural number, e, to the power of the parameter estimate.
A positive sign indicates a larger decrease in unemployment, thus more resilience.
The values shown for the spatial lag model are marginal effects, not coefficients.

Figure 5: Impact of telework on the change in unemployment from April to December 2020 at fixed broadband subscription levels



the earlier period ($\rho_{FebApr} = 0.414$,$\rho_{AprDec} = 0.151$).

Demographic characteristics also played a role in how unemployment rates recovered during this period. The percentage of the population with a college degree and identifying as multiracial appear to add to resilience, as increases in these variables led to higher rates of recovery. However, the percentage of the population under 18, Black, and Hispanic were associated with lower rates of recovery.

5 Conclusion

Understanding what factors contributed to the change in unemployment throughout the COVID-19 pandemic provides insight into the resilience of counties during this unique worldwide event. Industry composition and demographic characteristics were strongly associated with the change in unemployment in the southeastern region throughout the first 9 months of the COVID-19 pandemic. In the beginning stages, larger shares of employment in the manufacturing, leisure/hospitality, and information industry sectors were associated with increased unemployment. College education, the population under 18 and over 65, and the black population were associated with resilience during the first two months. This last result is consistent with Couch et al. (2020), who found that industry composition and employment in essential job functions protected black unemployment during the beginning stages of the pandemic. However, lower skills and occupational distribution resulted in greater job losses for minorities over time Couch et al. (2020). Many factors associated with the rise in unemployment from February to April also influenced the change in unemployment during the later April to December period. This indicates a level of vulnerability in communities exhibiting specific characteristics, but also suggests a level of resilience as they recovered much of that employment in the later months of 2020.

Our results show that telework ability was a crucial factor in changing unemployment levels during the pandemic, but local broadband adoption levels drive this relationship (Figures 4 and 5). From February to April telework had a positive impact, but only for counties with high broadband adoption. Counties with a high ability to telework, but low broadband adoption, were then held back in recovering from April to December. Thus, even if workers could work remotely, their home broadband situation may have prevented them from doing so.

This takeaway should serve as momentum for those pushing telework-friendly policies in both businesses and local/regional governments. It should also serve as evidence that recently enacted policies focused on improving broadband adoption (such as the Emergency Broadband Benefit (EBB) and its follow-on, the Affordable Connectivity Program (ACP)) are important for economic recovery. However, these policies were likely not implemented quickly enough to assist in the initial pandemic period when unemployment effects were acute or in the early months of recovery when they might have had the greatest impact. The EBB provided a discount of 50(75 on tribal lands) for broadband services among low-income households and was enacted as part of the Consolidated Appropriations Act in December 2020. Notably, the EBB only began distributing funds in May 2021, after the period assessed in this analysis. The program has been praised for its focus on adoption as opposed to simple availability Whitacre (2021) but also critiqued because it lacked funding for outreach Curi (2021). An expansion of the program (the ACP) was rolled out part of the infrastructure act that was signed into law in late 2021 Benton Institute for Broadband and Society (2021).

There are several limitations of this study that can be addressed in future research. Our empirical approach did not address causality of factors on unemployment levels. A significant variable does not mean that factor of interest caused the unemployment rate to change. Alternative methods such as two-stage least squares could be explored in future work. Although the spatial model addressed some of the omitted variable bias concerns, there could potentially be additional omitted variables (such as county or city-level COVID policies) causing biased and inefficient estimates. The study could be expanded into other regions, recognizing that the industry composition in the southeast may differ dramatically from other regions of the U.S. Finally, the results on broadband and telework open avenues of future research on the potential impact of expanded broadband adoption in rural communities, as companies appear to be maintaining telework policies and job flexibilities that could lead to migration into rural communities.

This research contributes an understanding of the factors that impacted the rise and fall in county-level 2020 unemployment rates during the pandemic. The results explain why some counties were more resilient and can help us appreciate how this unique event affected unemployment differently than past economic events. In particular, the occurrence of stay-at-home orders and disease suppression recommendations for businesses were unprecedented. While the results here suggest that high telework ability coupled with low broadband adoption levels slowed economic recovery, additional research should push for more insight into this finding. For example, surveys of workers who did (and didn't) work remotely during the pandemic would allow for a more nuanced discussion of the factors underlying individual decisions. The role of telework may well have permanently changed in light of COVID-19, and an improved understanding of the consequences of telework on unemployment changes will help set the stage for how the U.S. responds to future economic shocks.

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