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Is anybody home? remote working opportunities and employment during the covid-19 crisis

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Abstract

The article examines how the ability to work from home has impacted the level of employment across Metropolitan Statistical Areas (MSAs) in the United States during the COVID-19 pandemic. We use the share of jobs that can be performed at home and the ability of workers to work from home as measured by internet availability to show that both had a statistically significant impact on the level of employment. We control for the effect of the CARES Act and find that larger unemployment benefits reduced employment. Our estimations also indicate that as the share of essential workers decreased and the lagged number of COVID-19 cases increased, levels of employment increased. Restrictions in the form of stay-at-home orders, however, reduced employment.

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1. Introduction

The COVID-19 pandemic caused a record increase in the United States unemployment rate from 4.4 % in March 2020 to 14.7 % in April. Much of this increase was driven by stay-at-home orders that forced factories, retail stores, restaurants, and service providers to close. Some job functions can be performed at home such as educational services, finance, insurance, and the management of companies and enterprises. Other occupations cannot easily adopt a work from home model such as transportation, construction, accommodation and food services (Dingel and Neiman 2020). In attempting to determine the impact of the pandemic on the level of employment in a given community, we investigate the effect of the ability of employees to work from home and other factors on the level of employment in a metropolitan area. In a world where the possibility of another pandemic may lurk around the corner, this knowledge of the ability to work at home will give communities an idea of their degree of resiliency to future outbreaks. However, the ability to work from home is not solely determined by the function of a job. In order to successfully work from home many jobs require more than just a teleconnection; they also require an Internet connection. Approximately 12% of American households do not have Internet access[1] which would hinder their ability to stay employed during the transition from in-person work to work from home during the COVID-19 pandemic. To our knowledge, there is no research relating Internet access to its effects on employment. Therefore, this paper investigates those effects in order to shed light on the entire picture of teleworkability in the United States.

2. Model and Data

Our analysis focuses on metropolitan areas and the results should enable state and local governments to examine the impact of the virus on employment and take actions to reduce the impact of any future pandemic. Metropolitan areas can be viewed as both a labor market and an area with similarities in government services as well as COVID-19 infection rates. We use Census defined Metropolitan Statistical Areas (MSAs) which is a U.S. County or counties with a central city of at least 50,000, total population of 100,000 or more and all of the economically integrated contiguous counties. We were able to obtain data for 380 MSAs over eight months in 2020 after the pandemic arrived in the United States, April through November.[2] The result is a panel with data on the 380 MSAs for those eight months. We estimate a monthly employment index for each MSA using OLS multiple regression models.

In constructing our dependent variable, we took the number of people employed in each MSA (i) for each of the eight months (t) and divided it by the number of people employed in the MSA in 2019. That number was then multiplied by 100 and the result is:

$$\text{Empl Index}_{it} = (\text{Number Employed}_{it}/\text{Number Employed in } 2019_{i}) * 100$$

[1] See https://www.census.gov/content/dam/Census/library/publications/2021/acs/acs-49.pdf . Their data is for all households. Our study looks at metropolitan areas which tend to have higher rates of Internet connectivity than non-metropolitan areas. In our sample the mean share of households that lacked Internet access was 12.7%.

[2] There were 389 MSAs in the United States excluding Puerto Rico. We excluded NECTAs (New England City and Town Areas) where data were not available. Twin Falls, Idaho became an MSA in 2020 and some of the data are not available for that MSA and it is also excluded. Barnstable, Massachusetts had an error in the COVID data and was also excluded leaving us with a sample of 380 MSAs.

If there was no change in employment since 2019, the index for that month would have a value of 100, i.e., that month's employment was 100 % of 2019 employment. An index of 90 would mean a ten percent decline in employment.

Table I presents the mean monthly unweighted value of the index across the eight months in our study. The value of 85.5 for April 2020 showed employment levels on average almost 15 % lower than the average for 2019. The employment picture improved after that, reaching 96 % in October 2020 before declining a bit in November. In short, there was a major decline in employment at the start of the pandemic and our measure of employment had not recovered to 2019 levels by late 2020.

Table I: Mean Employment Index by month

Month	**Mean**
April	85.5
May	88.5
June	91.4
July	92.1
August	94.4
September	94.8
October	96.0
November	95.9

Employment Index is the MSA number of people employed in each month divided by the average number of people employed in 2019. Source: BLS data and authors' calculations.

The key variable of interest, *Telework*, is the share of jobs that can be performed at home. For example, if an occupation required driving a forklift, working on an assembly line, or working at a restaurant, these are tasks that could not be done from home. The variable we use is taken from the work of Dingel and Neiman (2020) who used responses to the Occupational Information Network (O*NET) covering work context and activities. They found that 37 % of jobs in the US could plausibly be viewed as being able to be done from one's home. The share of jobs in a metropolitan area that could be done from home ranged from 28 % in Cape Coral-Fort Myers, Florida, a travel destination with a great deal of employment in food preparation, to 51 % in San Jose-Sunnyvale-Santa Clara, California in the Silicon Valley.

There has been other work on the impact of the ability to work from home on employment. Montenovo et al. (2020) looked at data on individuals and found that job losses were greater during the pandemic in occupations that required more interpersonal contact and could not be performed remotely. Similar conclusions were reached by Brynjolfsson et al. (2020), Béland et al. (2020) and Crowley et al. (2020), among others.

The ability to work from home might also depend on Internet access. More than just a phone is required for many jobs that can be done at home such as web design or marketing. We use data from the U.S. Census to calculate the share of households in an MSA that lack Internet subscription service (*NoInternet*). To our knowledge, there are no other studies looking at the effect of Internet availability on employment controlling for other factors.

In late March 2020 the CARES (Coronavirus Aid, Relief and Economic Security) Act was signed into law. The Act created the Federal Pandemic Unemployment Compensation program that added $600 a week to regular unemployment insurance payments. Furthermore, independent contractors and other workers who were not eligible for regular unemployment compensation were made eligible under this program and states were given the option to drop the requirement that applicants must look for work in order to receive benefits (US Department of Labor 2020.) As a result, the mean benefit was over 105 % of the average wage for the months of April-July, reaching almost 130 % of the average wage for the three MSAs in Maine. Because of this, collecting unemployment benefits became attractive for some workers who could enjoy a higher income by accepting the payments and not working.

To measure the extent of this effect we used the replacement rate, that we define as the extent to which unemployment benefits replace wages. *ReplRate* is constructed as the average benefit in a state (plus $600 in each of the months April-July when the additional benefits were available) divided by the state's average weekly wage. We multiplied this number by 100 to create an index. A value of 110 would mean that the average benefit plus $600 would be ten percent greater than the state's mean wage. For MSAs in multiple states an average weighted by population share of the replacement rate was calculated. This issue has been examined elsewhere. Gupta et al. (2020) find that the negative employment effects were larger for workers in "non-essential"[3] industries although Bartik, et al. (2020b) found no evidence in support of the view that high unemployment insurance replacement rates drove job losses in early Spring 2020.

Some jobs are considered essential (*EssentiaPerc)* such as food sales, health care and public safety and must be performed regardless of the pandemic (Gascon, C. and Werner, D. 2020; Bartik et al. 2020a). Metropolitan areas with a larger share of such jobs would be predicted to have higher levels of employment as these jobs are ones that must be performed. We use occupation data from the Bureau of Labor Statistics Occupational Employment Statistics (OES) for May 2019 and categorize workers as essential by following the same methodology as Gascon and Werner (2020).[4]

The impact of COVID in the community would also influence employment. In areas like New York City and Seattle, which experienced a greater impact from the pandemic in April, there would be more closures and loss of work. To control for this, we looked at the previous month's level of COVID-19 cases per 1,000 people (*LaggedCase)* in each MSA through the employment survey week.[5] As the level of employment might drive the current case rate, we used the lagged rate instead. The rate was quite high at times, with the single highest monthly figure during the time period of our study occurring in Bismarck, North Dakota at a rate of over 125 cases per 1,000 people in November 2020. Earlier work such as Lozano Rojas et al. (2020), however, saw

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[3] It should be noted that some aspects of health care are considered essential yet could be performed from home, e.g., a radiologist.

[4] Occupational Employment Survey did not provide employment figures for every occupation for every MSA. Following a methodology similar to Gascon and Werner's we calculated the share of jobs that were essential by using 2018 employment share in each occupation of the MSA rather than 2019 as that was available for all MSAs. We then used Gascon and Werner's methodology to find the share that was employed in essential occupations.

[5] Data from https://github.com/nytimes/covid-19-data. The data were reported from state and local health agencies. Data were cumulative and the number of cases at the end of one month were subtracted from the number at the end of the previous month to determine the number of cases that month.

that an individual state's epidemiological situation had a comparatively modest effect on employment and Montenovo et al. (2020) found that job losses in Spring 2020 did not depend on the extent of exposure to COVID-19.

In March 2020, the vast majority of states adopted some type of stay-at-home order. Across the states these restrictions varied by industry, areas within a state, and how long various types of restrictions stayed in place. Further, there are not good measures of the extent of enforcement of these orders. Despite the limitations, we control for the impact of these stay-at-home orders through a *Restrictions* variable. The variable measures the number of days during the month a stay-at-home order was in effect. Similar to other variables for multi-state MSAs, the measure is an average weighted by the share of the MSA population residing in each state.

Many individuals in these heavily impacted areas utilized public transportation in their daily commute to work prior to the COVID-19 pandemic. During stay-at-home orders some firms transitioned to telework models. As a result, the ridership of public transportation has fallen, and U.S. transit agencies are projected to experience a shortfall of $23.8 billion (EBP US Inc. 2020). As public transportation was cut back some workers had difficulty getting to their jobs, and areas that had a large number of individuals using public transportation in their commute to work might experience lower levels of employment. The variable *PublicTrans* measures the share of workers 16 years or older who use public transportation in their commute to work.

Following Chandra et al. (2013) and Desmet and Wacziarg (2020), who show that density of population is an important determinant of severity of virus spread, we include the variable *Density* in our model. Although virus spread is captured by the variable COVID cases, it is possible that employers were more likely to either lay off or furlough workers in areas that were more densely populated and therefore more susceptible to further COVID spread.

3. Descriptive Statistics and Results

Table II presents descriptive statistics for the 380 MSAs in our study. As noted above, there was a large decline in employment from 2019 to April 2020 with incomplete recovery by November of that year. In looking at our independent variables we see a great deal of variation in the ability of workers to work from home. Although the average was 32.5 %, it ranged from 19.3 % in The Villages, Florida (a retirement community) to over fifty percent in some areas. On average, one in eight households lacked an Internet subscription. The mean level of essential employment was 15.9 % and ranged from 7.4 % of the workforce in Cleveland, Tennessee to over 30 % in a few MSAs.

Table II: Variable definitions, summary statistics and data sources

Variable	Definition	Mean	Minimum	Maximum	Source
Empl Index	(Number of people employed in each month) / (the average number of people employed in 2019)	92.3	63.4	107.9	Bureau of Labor Statistics
Telework	Proportion of MSA population able to work from home	32.5	19.3	51.9	Dingel and Neiman (2020)
NoInternet	Percentage of households without Internet subscriptions	12.7	3.2	29.1	U.S. Census Bureau
NoIntSq	Percentage of households without Internet subscriptions squared	179.1	10.1	848.5	U.S. Census Bureau
ReplRate	Unemployment benefits + 600 divided by average wage to account for the $600 stimulus amount	71.8	27.4	129.3	U.S. Department of Labor
EssentialPerc	Percent of jobs defined as essential	17.5	10.9	33.0	Bureau of Labor Statistics, Occupational Employment Statistics and Gascon and Werner (2020)
LaggedCase	COVID-19 cases per 1,000 people previous month	3.5	.00	36.8	*New York Times https://github.com/nytimes/covid-19-data* and U.S. Census
Restrictions	Number of days restrictions in Place for that month	5.6	0	31	*National Academy for State Health Policy https://www.nashp.org/2020-state-reopening-chart*
Density	1,000 people per square mile weighted by population in each census tract	2.4	.52	31.3	U.S. Census Bureau
PublicTrans	Share of population using public transportation to commute to work	1.6	.1	31.0	American Community Survey

The results of the multiple regressions are presented in Table III. Equation (1) shows the full model, equation (2) shows the model dropping the two variables that were not statistically significant at the 5 % level and equations (3) and (4) add in state fixed effects. We find that the share of the jobs in an area that could be done remotely, *Telework*, had a positive impact on employment across all of the regressions. If the share of the occupations where telework was possible increased by one percentage point, the Employment Index, the number of jobs during the pandemic month relative to 2019 average employment, increased by approximately one tenth of one percentage point. Although a teleworkable job could enable one to work from home during the pandemic, if the pandemic had not yet affected an area to a large extent, then the ability to telework would not impact employment much, which may explain the small magnitude of the impact.

Table III. Regression Results – Employment Index

Variable	(1)	(2)	(3)	(4)
Intercept	96.480*** (96.685)	97.129*** (105.882)	95.800*** (79.917)	95.821*** (79.928)
TeleWork	.106*** (6.458)	.105*** (6.534)	.089*** (5.883)	.086*** (5.740)
NoInternet	-.459*** (-5.639)	-.440*** (-5.481)	-.452*** (-5.685)	-.429*** (-5.512)
NoIntSq	.013*** (4.960)	.013*** (4.858)	.013*** (5.324)	.013*** (5.151)
ReplRate	-.044*** (-16.868)	-.045*** (-16.978)	-.054*** (-23.056)	-.054*** (-23.039)
EssentialPerc	.045* (1.730)		.195*** (7.823)	.196*** (7.849)
LaggedCase1000	.125*** (5.782)	.125*** (5.821)	.063*** (3.255)	.063*** (3.290)
Restrictions	-.190*** (-25.129)	-.189*** (-25.065)	-.177*** (-27.189)	-.177*** (-27.184)
Density	-.488*** (-8.258)	-.468*** (-12.473)	-.178*** (-2.980)	-.246*** (6.968)
PublicTrans	.017 (.326)		-.073 (-1.409)	
State Fixed Effects	No	No	Yes	Yes
R-Squared	0.437	0.437	0.620	0.620
Observations	3040	3040	3040	3040

***- Statistically significant at the 1 % level. *- Statistically significant at the 10 % level
t-ratios in parentheses below the coefficients.

The degree to which households in an MSA lacked a broadband Internet connection had a negative impact on employment, as expected. Even if a job could be done remotely in theory, the lack of broadband could render the possibility of doing so moot. We found that higher unemployment insurance benefits are associated with lower predicted levels of employment which is consistent with the idea that the temporary boost in unemployment benefits coupled with removing the requirement to look for work and extending the program to gig workers and the self-employed, did, in fact, lead to lower levels of employment.[6]

The effect of the share of employment in essential occupations on the employment index was not statistically significant at the 5 % level when state fixed effects were not included in the model but were significant when the state fixed effects were added in equations (3) and (4). When the share of jobs that were essential was greater, the level of employment was also greater.

The sign on our lagged COVID case variable was statistically significant but, contrary to our expectations had a positive effect. States with higher COVID rates in one month had higher levels of employment in the following month. Although we attempted to control for stay-at-home orders at the state level, the latter variable was imperfect and it is possible that looser orders or less rigorous enforcement of the orders led to more COVID cases and also greater levels of employment in the following month.[7] Despite the limitations of our restriction variable, *Restrictions*, when stay-at-home orders were in place employment declined. The effect declined by less than ten percent when we added in the state fixed effects, showing that restrictions did affect employment. Greater density did reduce employment during the pandemic, ceteris paribus, but the share of workers using public transportation did not.

The model without fixed effects explained approximately 43% of the variation in the employment index across the MSAs and with fixed effects 62% of the variation was explained. In running F-tests, we found that we could drop the percentage employed in essential occupations and the share of the population using public transportation from equation (1) without fixed effects, even though the former was statistically significant in the fixed effects equations. It should be noted that all of the variables were statistically significant at the 1 % level with the exception of the share of workers in essential industries in equation (1) and the public transportation variable.

4. Conclusion and Implications

The impact of the COVID-19 pandemic in the United States goes beyond infections, hospitalizations and deaths. In this paper we focus on the impact of the pandemic on the level of employment across MSAs and in particular, we investigate the effect of the ability of employees to work from home. We find that the ability to work from home proved to be a statistically significant factor in an area's employment level compared to the pre-pandemic year of 2019. A one percentage point increase in teleworkability increased the employment in the same area by about one tenth of a percent. A lack of Internet access proved to be an important determinant of employment with each additional percentage point of the population lacking Internet access reducing employment by almost one half that amount. To our knowledge, this is the first paper to relate Internet access and the employment rate during the pandemic. Further, employment loses were mitigated by having more essential workers when controlling for state effects. It is

[6] It is possible that the intent of the $600 bonus was in fact to keep potential workers home during the pandemic. In any event, higher unemployment benefits resulted in lower employment levels.
[7] We would like to thank an anonymous referee for this point.

for others to discuss whether stay-at-home orders were worthwhile, but we show that such restrictions did reduce employment.

It is clear that there has also been a large shift in the landscape of the working world. The fear of infection has been driving people away from the traditional in-office working model in favor of working from home and, in some cases, not working at all when unemployment insurance benefits can be larger than paychecks. For jobs that are transferable to a work from home model, there was essentially a supply shock to the teleworking model as many employees made the switch to working at home. However, the nature of a given job and an employer's permission to telework are not the sole determinants of whether a person can in fact work from home. Access to the Internet plays a role and given that one in eight households in the United States does not have access, this can limit employment during a pandemic where non-remote work might not be a possibility. For these individuals, working from home might not have even been an option and so, we see lower levels of employment in areas with a higher percentage of households lacking Internet access.

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