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Labor Market Effects of Local Spread of COVID-19

Michael Dalton, U.S. Bureau of Labor Statistics

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Keywords: COVID-19, coronavirus, recession, unemployment

Labor Market Effects of Local Spread of COVID-19*

Michael Dalton†

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Abstract

This paper explores the short-term local labor market impact of the spread of COVID-19 in the United States, using the Current Employment Statistics survey and the Current Population Survey microdata. It uses the longitudinal aspect of both these surveys to measure changes in employment for business establishments and household members. I match the survey respondent to the measured local incidence of confirmed COVID-19 cases, using confidential information on county of location, to estimate the impact of the local incidence of the virus, after controlling for multiple measures of government intervention. I find the greatest declines in employment in counties with higher incidence of COVID-19. These effects vary by industry: leisure / hospitality and other services have large declines in employment relative to the effect of the incidence of the virus, while the employment decline in construction and transportation and warehousing depends more on the local incidence of the virus. Finance / insurance, a very telework-friendly industry, is unaffected by the incidence of the virus. These short-term employment effects have implications for future employment patterns as government restrictions are relaxed and business owners begin to decide whether to open their businesses while the virus is still active in the United States.

JEL codes: J01, J21, J63

Keywords: COVID-19, Coronavirus, Recession, Unemployment

† Bureau of Labor Statistics, 2 Massachusetts Ave NE, Washington, DC, 20002, 202-691-7403, dalton.michael@bls.gov. Opinions expressed here do not reflect those of the federal government or the Bureau of Labor Statistics.

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1 Introduction

The spread of COVID-19 has had a sudden and historic impact on the United States labor market. Through depressed demand from consumers choosing to stay home, government mandates for businesses to close, supply chain and shipping disruptions, and income losses and greater uncertainty leading to further declines demand, the negative effects on the economy are extremely broad. While the significance of the initial employment collapse is clear, the path of the recovery is less so. We do not know how the labor market will respond as government restrictions are lifted and businesses are urged to open and employees to return to work while the virus continues to spread. Concerns about the safety of employees and customers and the hesitancy of consumers to return to their prior spending patterns is creating a great deal of uncertainty about which jobs are likely to return quickly, and which jobs are most sensitive to local ebbs and flows of virus incidence.

There is already some evidence that government shutdown orders alone do not explain the pattern of the recession. Chetty et al (2020) find that individuals began changing behavior—with both consumer spending and employment falling—prior to state governments issuing shutdown orders. This shows that individuals are responsive to information about the virus, even if the government is not immediately acting. Baek et al (2020) find only 25% of unemployment claims can be explained by the implementation of stay-at-home orders. To the extent that living in a location where the virus is spreading makes the virus more salient in affecting behavior, local spread may have localized impacts on employment and economic activity. Furthermore, the incidence of the virus also affects both the perceived and real probability of getting the virus oneself. This suggests other channels affecting employment need to be thoroughly examined.

While population density, climate, humidity, and local government action are potential contributing factors to the spread of the virus, the exact path of the virus through individual locations cannot be clearly predicted. Thus, the relationship between employment change and the timing and scale of the spread of the virus thus far can be used to study what people and what jobs may have difficulty returning as the economy re-opens – and which jobs may fluctuate in response to the contemporaneous local incidence of the virus.

To understand the relationship between employment change and the local spread of the virus, this paper attempts to separate out the employment impact of the Covid-19 pandemic into a local component from a more aggregate impact combining a nationwide component and effects from local government mandates. Past and recent research has tried to estimate the extent that labor markets are localized, as opposed to national. Manning and Petrongolo (2017) find that policies and individual behaviors are at least partially bounded by the borders of the local labor market, suggesting that an unexpected event, such as the broad economic impact of the spread of the virus, will have localized effects on the labor market separate from the effect on the entire country. Most research thus far on the labor market impact of the virus has focused on broader impacts, which have been large: Kahn et al (2020) estimate a 30% decline in online job postings across the United States; Loewenstein and Dey (2020) estimate that the workers in the bottom quintile of wages make up over half of the employment in industries particularly exposed to the virus; Barrero et al. (2020) estimate that 42 percent of recent layoffs will result in permanent job loss. By separating out the larger, broad effect and the effect of local government intervention from the local effect on employment, this paper gives insight about which jobs are most at-risk of sustained employment loss and which jobs are at-risk for more uncertainty in the coming months.

To do this, I measure the number of cases of COVID-19 per capita in a county as of the reference period in the surveys, and combine this with longitudinal employer and employee histories in the microdata of the Current Employment Statistics (CES) survey and the Current Population Survey (CPS). These allow me to observe changes in employment at the establishment (for the CES) and individual (for the CPS) levels. Additionally, I construct measures at the county level to control for government-mandated restrictions in order to address the potentially confounding impact on employment and spread of virus. Relying on the randomness of the timing and extent of the local spread of the virus, focusing on changes at the microdata level, and using data from previous months, I estimate which parts of the changes in the local labor markets can be attributed to the local spread versus the broad economic impact and government interventions. I then use these estimates to assess how the impact of the virus on local employment varies by industry.

1.1 Data

Incidence of COVID-19 at the county level is acquired from the New York Times, which provides daily updates[1]. The number of cases reflects positive test results as reported from individual states and the Center for Disease Control and Prevention (CDC). The per-capita measure is calculated using county-level population data from the 2010 Decennial Census. The areas with the highest incidence as of April were in the northeast, the south, dotting around the Great Lakes, and the southwest. While the hardest hit areas tended to be densely populated areas, there is still variation as some rural areas (e.g., Dakota county, Nebraska) were especially hard hit, and some dense urban areas (e.g., the Bay Area) did not have a high incidence of the virus. This geographic variation will be useful in analyzing the effects of the virus on the labor markets.

To observe employment changes at the establishment-level, I use the Current Employment Statistics (CES)[2]. This is a monthly survey of establishments that asks about number of employees, hours worked, and aggregate earnings of workers. The CES has a panel design that surveys most establishments for typically more than 24 consecutive months. As a result, changes in employment from one month to the next can be estimated at the establishment level in the CES microdata. Additionally, using these microdata allows me to match establishments with county-level COVID-19 information. The reference period for the CES survey is the pay period that includes the 12th of the month. For this reason, I use the measure of confirmed COVID-19 cases per capita in the county as of the last day of the week for the most recent reference period.

The map in Figure 1 shows the change in employment across establishments within a MSA from March to April 2020[3]. Some patterns are readily apparent: darker shading in the northeast, around the Great Lakes, the southern tip of Florida, the southwest, and a few patches along the west coast. Comparing to a map of COVID-19 incidence (Figure B1), there is a clear correlation between higher incidence of COVID-19 and greater decline in

[1] Available at https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html (The New York Times, 2020). Last accessed May 31, 2020.

[2] For information about the CES, visit https://www.bls.gov/web/empsit/cesprog.htm.

[3] MSA definitions based on Bureau of Labor Statistics definitions: https://www.bls.gov/oes/current/msa_def.htm

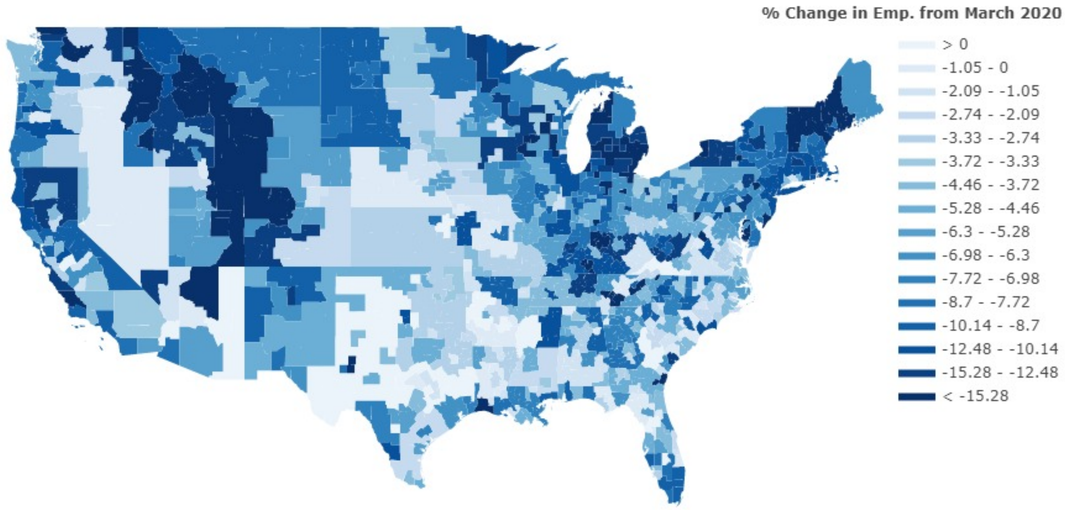


Figure 1: Change in employment in MSAs in April 2020, Current Employment Statistics

employment at the establishment level.

To examine employment effects for individuals, I use the Current Population Survey (CPS). This is a nationally representative monthly survey of 60,000 households, asking a variety of questions that cover demographic and labor force concepts. The labor force questions are also primarily focused on the week that including the 12th day of the reference month. Like the CES, the CPS has a panel aspect. In any given month, approximately 75% of the households sampled were also sampled the previous month. This longitudinal aspect allows for observing transitions in labor market status from one month to the next[4]. I match households to their county of residence to estimate how the local incidence of COVID-19 is related to labor force transitions for these surveyed individuals.

A confounding aspect in studying the relationship between COVID-19 incidence and changes in employment is the extent of simultaneous government intervention. While it is difficult to get a consistent quantitative measure of the extent of any intervention across counties and states, the New York Times provides some data about "stay-at-home" orders for states and counties[5], based on primary sources from governments. Using this information,

[4] For more information about the CPS, visit https://www.bls.gov/cps/documentation.htm

[5] An archive of stay-at-home orders are reported here: https://web.archive.org/web/*/https://www.nytimes.com/interactiv stay-at-home-order.html

the date of first stay-at-home order is determined for each county[6]. For 32 states, the first stay-at-home order is the same for all counties, as it was mandated at the state level. For the remaining states, some counties acted before the state as a whole. For instance, Oklahoma never made an official stay-at-home mandate, though some counties within Oklahoma chose to make these orders separately. The number of weeks between the first government mandate for the county and the reference period for the surveys is the key control for local shutdowns[7].

Timing of stay-at-home orders may not be the only dimension that governments have restricted economic behavior. I add an additional measure of intervention based on anonymized data published by Google at the county level that measures mobility [8]. The data made publicly available is a measure of the number of visits to specific types of establishments by day, relative to a benchmark set in January 2020. This paper uses the retail space (e.g., visits to movie theaters, restaurants, museums, and shopping centers) mobility measure. The sample of individuals used to create the data are people who choose to have their location history on while using Google services. The representativeness of the sample is not defended by Google, and due to the anonymized nature of the data, it cannot be validated as representative of the population. However, the overall patterns observed in the data are intuitive, suggesting this may be a good approximation for movement relative to businesses. There is an across-the-country steep decline in visits to retail spaces, with an even larger decline in many areas that had a higher incidence of the virus. By combining measures of government limiting movement from home (length of stay-at-home order) and limiting businesses (decline in visits to retail), both sides of the potential impact from government interventions on employment are being captured[9].

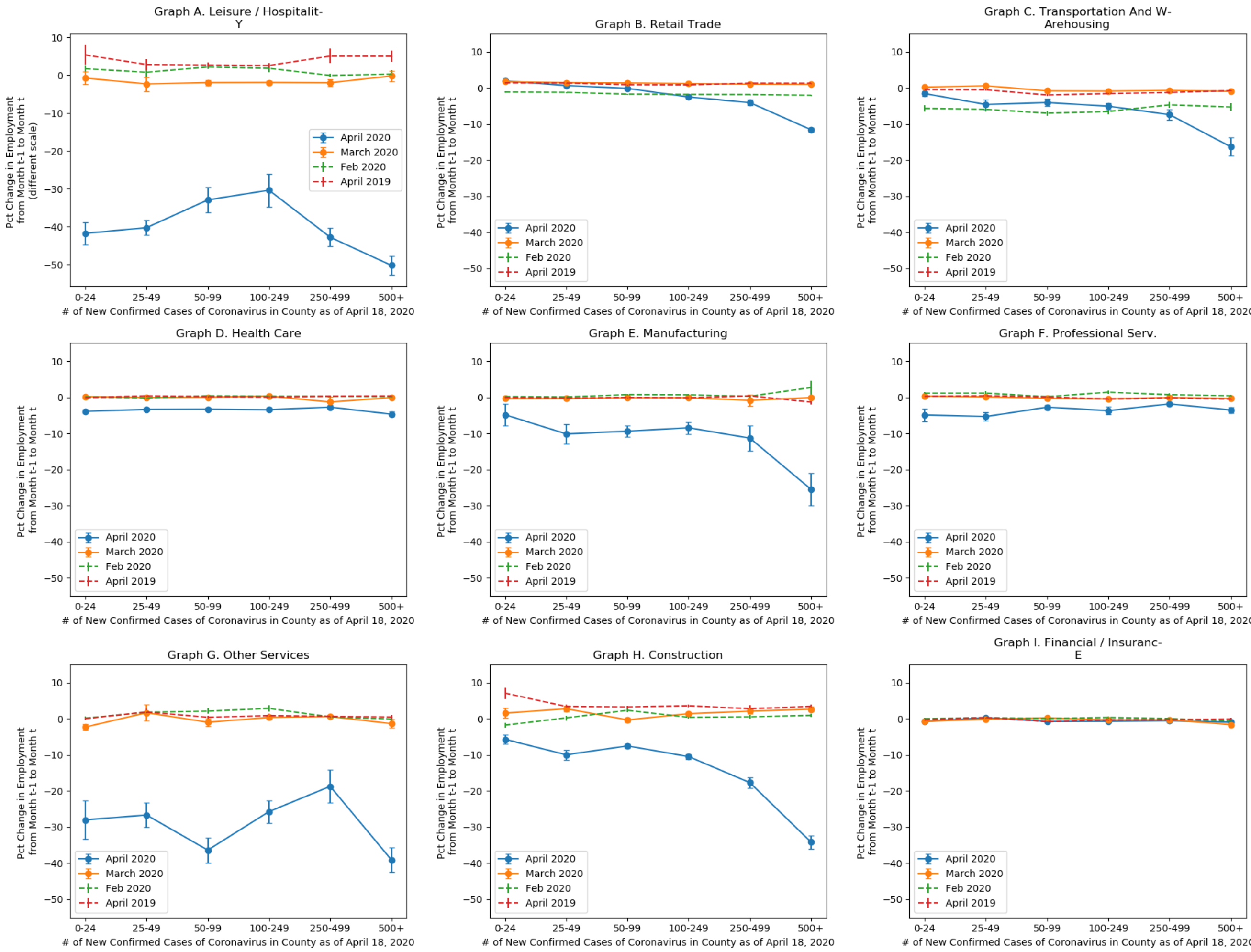
[6] Stay-at-home orders are treated the same as "shelter-in-place", "lockdown", and "shutdown" orders.

[7] Figure B2 shows the number of days prior to April 18th that the county had a stay-at-home order.

[8] Google LLC "Google COVID-19 Community Mobility Reports". https://www.google.com/covid19/mobility/ Accessed: May 31st, 2020.

[9] Figure B3 shows the mobility measure as of March 14th, 2020 (Panel A) and April 18th, 2020 (Panel B).

Figure 2: Decline in Employment in April 2020 as COVID-19 Increases, by Industry



2 Labor Market Consequences of Spread of Virus

2.1 Analysis of Current Employment Statistics Microdata

2.1.1 Graphical Analysis

In each panel of Figure 2, there are plots of four separate months of data from the CES, with the horizontal axis showing the number of confirmed cases of COVID-19 per 100,000 residents at the county level, and the vertical axis showing the average percentage change in employment across establishments in that bin, weighted by establishment employment. Including April 2019 helps identify any monthly seasonal effects that may confound the analysis, and April 2019 works well as a control month as it definitively is unaffected by COVID-19.

For most industries, there is an overall shift downwards of the April 2020 line relative to the other three months of data. This shift can be thought of as the broad economic impact of COVID-19 faced by all geographies, and the gradient of the line as the additional impact due to local incidence of the virus. However, there are confounding factors, such as government intervention, that muddle the interpretation of the gradient. This will be addressed more directly in the following section and these graphs are meant for illustrative purposes of overall patterns.

Figure 2 makes clear that the effects of the pandemic on employment thus far are very heterogeneous. Leisure/Hospitality has the biggest shift downward, bottoming out at 49% decline in at the highest incidence rate in April 2020. The other services industry (NAICS code 81) also has a big shift downwards, and, within this sector, the industries with the largest declines in employment are nail salons, personal care services, beauty salons, and barber shops. Manufacturing and construction both have notable downward shifts and a negative trend as the incidence rate increases. Retail trade and transportation and warehousing do not appear to have much of an overall shift but do have a trend downward as the incidence rate increases. The finance and insurance sector appears unaffected in both shift and trend.

2.1.2 Econometric Model

The next step in the analysis is examining these patterns in a more rigorous regression framework to address potentially confounding factors. The primary confounding factor is that government interventions are likely to impact both the economy and the spread of COVID-19. For instance, if an area were to shut down completely and with full compliance from the residents, we may expect the incidence to be low in that area while employment would be drastically reduced, too. In this example, the concepts are statistically related, but the incidence of the virus is not the immediate causal relationship. I include 2 measures to control for government interventions: the county-level measure of number of days since a stay-at-home order went into effect is included in the model and the mobility measure on change in visits to retail spaces. All official stay-at-home orders occurred after the March 2020 reference period, so will only have positive values for the April 2020 respondents. For the Google mobility measure, April 2019 is assumed to have no change relative to Google's chosen benchmark of January 2020. These measures work as good proxies for government intervention because they cover both the impact on individuals' movement from home (stay-at-home orders) and the consumers relationship to businesses (visits to retail). One thing to note is that the mobility measure may actually be controlling for some of the effect of the incidence of the virus on economic activity, which will attenuate the estimated effect of the incidence downward. Holding government intervention constant, one channel through which living in an area with a higher incidence of the virus can affect employment would be a drop in demand resulting from consumers choosing not to visit the stores. This illustrates the difficulty in estimating this impact: the virus has hit so quickly that it is difficult to untangle these different causal pathways. For this reason, the analysis errs on the side of caution of including the mobility measure that may attenuate the results on local incidence.

A second confounding factor is that certain geographic factors may affect both the spread of the virus and the change in employment (e.g., population density, climate, industry mix within sectors, and other unobserved characteristics). Figure B4 already illustrates that the differences between months of data cannot be explained fully by common patterns in geographic areas that had a higher incidence rate as of April 2020 since April 2019 does not reflect the same trend as April 2020. MSA fixed effects in the regresson control for both observed and unobserved factors that are common across areas, and will make sure the relationship between change in employment and incidence of virus is not solely explained by local characteristics of MSAs. Furthermore, dummies for each month in the analytical sample and additional controls for firm size, industry, population of county and whether the establishment is part of a multiunit firm are included.

$$\begin{aligned}\Delta employment_{ict} = \sum_t \alpha_t + \beta COVID_{ct} + \\ \gamma_0 DaysSinceMandate_{ct} + \gamma_1 DaysSinceMandate_{c^*t} \\ \delta Mobility_{ct} + \\ \sum_m \theta_m I(c \in m) + \mathbf{X_{ict}}\sigma + \epsilon_{ict}\end{aligned} \tag{1}$$

Equation 1 shows the regression model to be estimated, where

- $\Delta employment_{ict}$ is the change in employment from the previous month for establishment i in county c at month t,
- α_t is the month-specific national effect for month t[10],
- $COVID_{ct}$ is the county-level COVID-19 number of cases for month t per 100 residents,
- $DaysSinceMandate_{ct}$ is the number of days since a stay-at-home mandate in county c as of month t,
- $DaysSinceMandate_{c^*t}$ is the average number of days since a stay-at-home mandate in the counties within 30km of county c as of month t,
- $Mobility_{ct}$ is the Google mobility measure as of the reference date for month t, which can take a value between 100 and -100 and is a benchmark relative to visits to retail spaces in January 2020,
- $I(c \in m)$ represents an indicator for county c being in MSA m,
- X_{ict} represents the vector of control variables specific to establishment i in county c in month t, and
- ϵ_{ict} is the idiosyncratic error term.

The key estimate of interest is β. The local government intervention effects are captured by γ_0 and δ, and the broad national impact is captured by $\alpha_{April2020}$. For the regression, $COVID_{ct}$ is the number of cases in county c in the 4 weeks leading up to (and including) the end of the reference period in month t. The interpretation of β is relative to recent cases, which would allow for a county to have an improving (or worsening) incidence rate for future months when applying the estimates to new data.

For $Mobility_{ct}$, there are some gaps in the data for some counties due to lack of available data to construct the anonymized measures by Google. The rolling average for a county across the nearest date to the reference period is used. For counties with no data near the reference period, the state average on that date is used to fill the missing value for the county.

[10] $\alpha_{April2019}$ is left out of the estimation so that the coefficients α_t estimates are relative to April 2019.

2.1.3 Regression Results

Table 1 shows the results for the full sample and by industry of the full model depicted in equation 1[11]. The sample includes establishments responding to the CES in consecutive months for April 2019, February 2020, March 2020, and April 2020. Each row in the table shows results from a separate regression, where the goal is to estimate the slope on per capita incidence of COVID-19 at the county level (β) and compare it to the effects from the size of the national effect ($\alpha_{April2020}$) and the proxies for local government intervention effects (γ_0 and δ). The aggregate effect shown in the second column is for an establishment in April 2020 and assumes the establishment is in a county that has had 3 weeks of a shutdown and 30% fewer visits to retail spaces relative to the baseline. The p-value underneath the effect is for the F-test of the linear combination of the coefficients being different from zero:

$$\alpha_{April2020} + 3 \times \gamma_0 + (-30) \times \delta = 0 \tag{2}$$

For the full sample, an establishment in a county going from 1% of the population with a confirmed case of COVID-19 in the previous month to 0% will have a 4.3% increase in employment. The estimated aggregate non-incidence effect gives a decline in employment of 7.4%. A 4.3% improvement in employment relative to the 7.4% aggregate, non-incidence effect is very large, economically significant, and statistically significant. This shows the important role of controlling local virus transmission in protecting against further employment declines.

[11] For each month, the Saturday of the week of the reference period (12th of the month) is used to determine the number of COVID-19 cases. For April 2019, 0 cases are reported. As of February 15th 2020, 9% of establishments were in a county with at least one confirmed case. As of March 14th 2020, 57% of establishments were in a county with at least one confirmed case. As of April 18th 2020, 99% of establishments were in a county with at least one confirmed case.

Table 1: Heterogenous Impact of Local of Spread of Virus, Current Employment Statistics survey

	Dep. Var: Percent Change in Employment from Previous Month		
Sample...	Effect of COVID-19 Cases per 100 in County	Aggregate Impact Separate from Incidence	Sample Size
...Full Sample	-0.043 (0.0022) [<.001]	-0.074 [<.001]	735725
...Leisure/Hospitality	-0.056 (0.0091) [<.001]	-0.38 [<.001]	63375
...Retail Trade	-0.041 (0.0034) [<.001]	-0.01 [<.001]	254757
...Transportation and Warehousing	-0.039 (0.0089) [<.001]	-0.036 [<.001]	30311
...Health Care	-0.031 (0.0072) [<.001]	-0.1 [<.001]	52363
...Manufacturing	-0.082 (0.016) [<.001]	-0.096 [<.001]	28824
...Professional Business Services	-0.026 (0.0093) [0.0056]	-0.053 [<.001]	37132
...Other Services (except Public Admin)	-0.056 (0.017) [0.0011]	-0.23 [<.001]	18242
...Construction	-0.13 (0.009) [<.001]	-0.1 [<.001]	54187
...Finance and Insurance	0.0011 (0.0019) [0.58]	-0.011 [<.001]	98980

Each row is a separate OLS regressions, with robust standard errors are in parentheses and p-values are in square brackets. Sample includes all establishments with valid responses for the variable in both the response month and previous month from April 2019, February 2020, March 2020, and April 2020. Included in each regression are the controls for government interventions. The second results column represents the estimated employment effect for a county with 3 weeks of stay-at-home orders and a 30% decline in visits to retail establishments in April 2020. Additional controls are fixed effects for MSA, firm size, industry, whether the establishment is part of a multi-unit firm and population of county.

The industries with the largest magnitude drop in employment separate from incidence are leisure / hospitality and other services with 38 and 23% declines in employment in April 2020, respectively. The largest slope with respect to the incidence of the virus is construction, with a coefficient translating to a 13% decline in employment for every 1% of the county population that is confirmed with the virus in the preceding month. The only industry with a null effect on the incidence of the virus is finance / insurance. Additionally, finance is the only industry where the effect of number of days since a mandate also has a null effect on employment. One potential explanation for these results is that telework is common in finance, resulting in less of an impact from the virus itself, and any employment loss in April 2020 is based around broad economic trends for this industry. Construction, on the other hand, is not telework-friendly, so this may partly explain why it has the largest response to local virus incidence. Also, some construction jobs may involve being in close proximity to customers' homes (for instance, home remodeling), and customers choose to forgo these jobs to avoid contact.

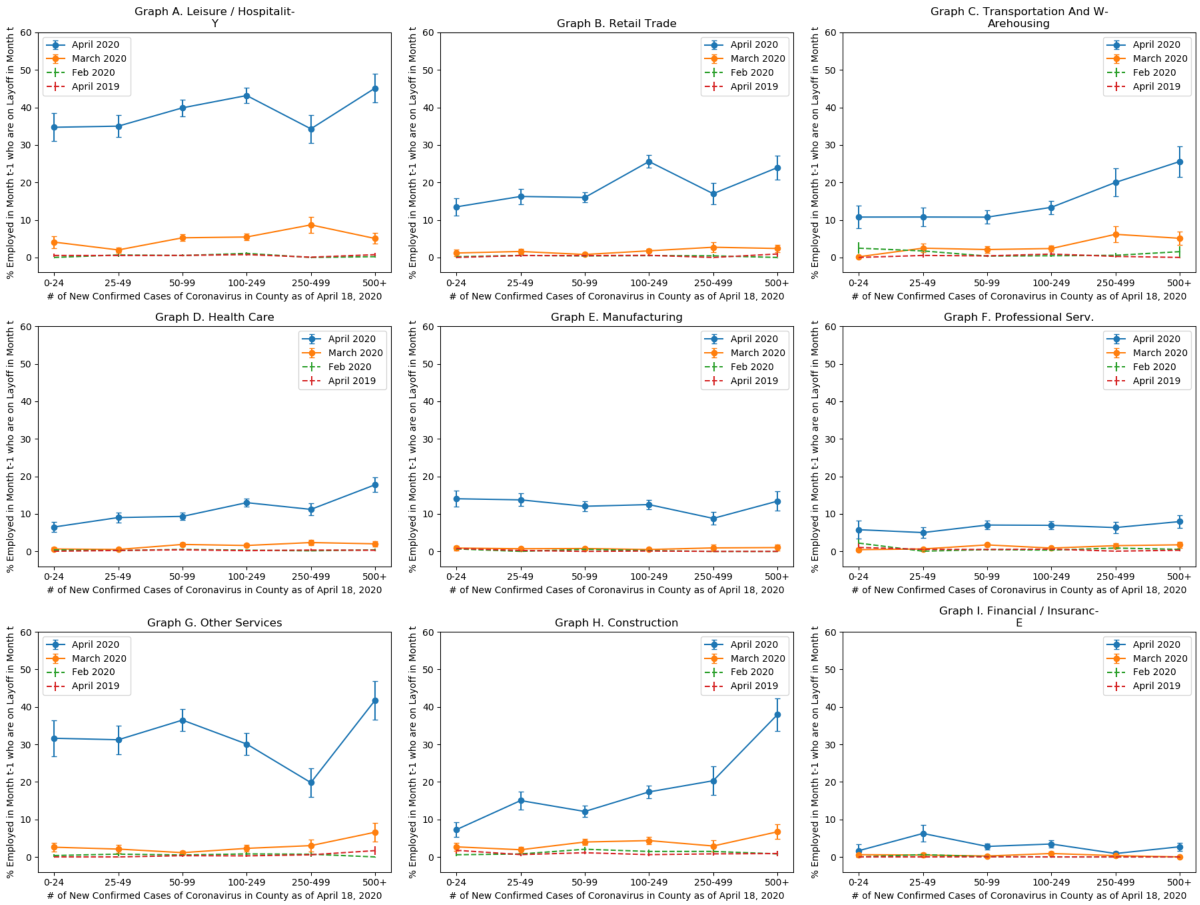
Comparing the ratio of the local incidence effect relative to the separate, aggregate employment impact provides insight into the industries that may return quicker as the virus subsides locally, but also means there is more uncertainty looking into the future as the employment will fluctuate in sync with the return of the virus. Creating the ratio by dividing the first column estimates with the second column estimates, construction, transportation and warehousing, and retail trade have a ratio greater than 1. This means 1% of the county's population having confirmed cases of COVID-19 will have a bigger impact on the industry's employment than the separate aggregate effect. It is likely that employees in these industries may benefit the most from getting the spread of the virus under control locally.

2.2 Employment Changes Within Households: Analysis of Current Population Survey microdata

Similar patterns between the household survey and establishment survey are observed. Figure 3 shows the percentage of respondents who were employed in the previous month and were then on layoff in the current month[12]. On layoff is the most common labor force tran-

[12] On layoff also includes respondents who were listed as "employed but absent" and gave a reason for their absence as some "other" reason. In April 2020, a number of respondents gave a response that COVID-19

Figure 3: More Workers Leaving Employment as COVID-19 Spreads, by Industry



sition state for those leaving employment in the previous month in the CPS. A large shift upwards can be seen for April 2020 for many industries. Similar patterns emerge as in the CES: construction has a steep gradient transitioning from employment to on layoff as the county has more COVID-19 cases, and transportation and warehousing also shows increasing loss of employment as the incidence increases. The biggest upward shifts in lines for April 2020 are in leisure / hospitality and other services.

An analogous regression model to that of equation 1 is used for the CPS, instead modeling the likelihood that respondent i employed in the previous month will be on layoff in the current month. For these regressions, I use data from the same months as the CES– April 2019, February, March, and April 2020, restricting the data to respondents 16 and older

was the reason for their absence, which should include the respondent in the "on layoff" category. In order to not miss this group in the analysis, they are included for all months with the "on layoff" unemployed respondents.

employed in the previous month[13]. The only other difference are the basic controls included in the $\mathbf{X_{ict}}$ of equation 1: person-level controls for gender, race, age, education, occupation, industry, in addition to MSA fixed effects and county population.

[13] 8%, 57%, 99% of the respondents were in a county with at least one confirmed COVID-19 case in February, March, April 2020, respectively.

Table 2: Heterogenous Impact of Local of Spread of Virus, Current Population Survey

	Dep. Var: Y/N Respondent is on Layoff		
Sample...	Effect of COVID-19 Cases per 100 in County	Aggregate Impact Separate from Incidence	Sample Size
...Full Sample	0.018 (0.0061) [0.0036]	0.14 [<.001]	149291
...Leisure/Hospitality	0.0004 (0.029) [0.99]	0.39 [<.001]	11951
...Retail Trade	0.025 (0.029) [0.39]	0.16 [<.001]	14596
...Transportation and Warehousing	0.15 (0.042) [<.001]	0.11 [<.001]	6641
...Health Care	0.014 (0.013) [0.29]	0.1 [<.001]	20373
...Manufacturing	-0.0021 (0.022) [0.92]	0.14 [<.001]	14344
...Professional Business Services	0.036 (0.02) [0.07]	0.064 [<.001]	11848
...Other Services (except Public Admin)	-0.033 (0.043) [0.45]	0.28 [<.001]	6169
...Construction	0.13 (0.036) [<.001]	0.12 [<.001]	9888
...Finance and Insurance	-0.00041 (0.0092) [0.96]	0.043 [<.001]	6990

Each row is a separate OLS regressions, with robust standard errors are in parentheses and p-values are in square brackets. Sample includes all establishments with valid responses for the variable in both the response month and previous month from April 2019, February 2020, March 2020, and April 2020. Included in each regression are the controls for government interventions. The second results column represents the estimated employment effect for a county with 3 weeks of stay-at-home orders and a 30% decline in visits to retail establishments in April 2020. Additional controls are fixed effects for MSA, gender, age, education, occupation, industry, and population of county. Results are weighted by CPS person weights.

Table 2 shows the results from the separate regressions by industry of employment in the previous period, analogous to the CES results in Table 1. Similar to the CES results, the biggest aggregate effects separate from the incidence are in the leisure/hospitality and other services industries. Examining the gradient on the incidence of the virus by industry, construction again has one of the larger effects in the CPS data: an increase of 1% of the county population confirmed getting the virus in the month leads to an 13% increase in the probability of going from employed to on layoff for workers in construction; this matches the 13% decline in employment for establishments in this industry observed in Table 1. In addition to construction, transportation and warehousing also has a large negative impact on employment of local incidence relative to the aggregate effect in both the CES and CPS, with ratios larger than 1. Lastly, finance / insurance is the only displayed industry with a null impact of the spread of the virus in both the CES (Table 1) and CPS (Table 2).

3 Discussion

The common results between the CES and CPS tell an important story: not only was there a broad negative impact on employment due to COVID-19 in April 2020, but this impact was worse in local labor markets with a higher incidence of the virus. Variation in these patterns between industries provides suggestive evidence about which jobs may return in the short- or medium-term as the spread of the virus continues to be uneven throughout the country. Leisure / hospitality and other services are the sectors with the highest employment decline in employment relative to the effect of the incidence of the virus, and are likely to have a slower recovery of employment even as the incidence is reduced and lockdowns begin to be lifted. Some industries may have more uncertainty attached to them as their employment is dependent upon the local spread of the virus – construction and transportation and warehousing have the largest negative effect of the local incidence of the virus relative to the aggregate, separate employment impact in both the CPS and CES. The industry with the smallest employment declines –in terms of local impacts – is finance / insurance.

Dingel and Neiman (2020) estimate that finance / insurance and professional services have some of the highest proportion of telework-eligible employees . Telework allows the employees to continue doing their jobs without compromising the health of employees or customers, and are less likely to be impacted by government stay-at-home orders. As seen in both data sources, these industries have been minimally impacted. As long as the demand holds steady, the impact of COVID-19 will continue to have the smallest effect for these industries, though uncertainty remains surrounding demand the future of demand.

Leisure / hospitality and other services are industries that are cyclical, as demand tends to decline for these industries during recessions. A decline in employment for these industries can be partially explained by a drop in demand resulting from more income uncertainty of consumers as confidence in the economy has taken a sharp decline[14]. Also, both of these industries rely heavily on in-person interactions with the customers. With the growing health concerns and struggle to find ways to maintain the customer base in a safe way, these industries may be slower to recover even as the virus is more under control. The amount of demand that returns to industries may be a good indication about the duration of impact that COVID-19 will have on the economy.

Construction and transportation and warehousing may be more prone to having individual worksites shut down due to illness, instead of being shut down across the entire industry. Though these industries are not very telework friendly, for many of the occupations, employees can primarily do the same jobs without direct contact with customers. The risk is primarily contained to only employees interacting with one another, which may explain why these jobs have more resiliency when the incidence of the virus is low.

This paper estimates the relationship between local employment changes and the number of local confirmed cases of Covid-19. The interpretation of these coefficients may change as testing becomes more widespread and the proportion of confirmed cases to actual cases approaches 1. As a result, this methodology may over-estimate the relationship between employment impacts and cases of the virus. As of April 2020, many cases are unconfirmed because a number of people who are infected are not getting tested, or are asymptomatic and never seek out testing. Thus, the coefficients presented here should be considered as an upper bound for the impact of additional confirmed cases on employment, as testing becomes more

[14] https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/survey-us-consumer-sentiment-during-the-coronavirus-crisis

widespread and a higher proportion of people who have the virus are tested. The extent of this estimation issue is not clear[15]. Conversely, it is possible that the behavioral effects are strictly based on salience of COVID-19 – regardless of the number of unconfirmed cases, more confirmed cases is what drives behavioral changes, in which case, the coefficients are not overestimated.

Going forward, examining other dimensions of business decision making in terms of how the payroll responds to changes in COVID-19 will be valuable to understand the dynamics that are occurring in the labor market. Additionally, analyzing how these dynamics relate to firm size and local geographic concentration of industries will help elucidate the future of the labor market through the remainder of the pandemic and after.

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[15] Estimates of the gap is between confirmed positive cases and actual infections vary widely. For example, one estimate from a company that tested raw sewage for COVID-19 says that there was about a 4:1 ratio of infections to confirmed positive tests https://www.sun-sentinel.com/coronavirus/fl-ne-coronavirus-miami-dade-tracking-spread-via-sewage-20200501-2fwgszzckjfc3get3frfrhw33a-story.html

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Appendix to Dalton (2020) "Labor Market Effects..."

A Additional Tables

These tables show the building up of the full model depicted in 1. The first row restricts all coefficients to zero except for β. The second row restricts the coefficients on γ_0, γ_1, and δ to be zero. The third row includes γ_0 and γ_1 in the estimates, and the following row estimates the full model. As a robustness check, the last row removes the New York City-specific counties.

In Table A1, the coefficient for the national effect in April 2020 is cut in half when controlling for number of days since the county shut down, and then cut in half again once controlling for state-COVID-period fixed effects. This implies a large portion of the impact of the national trends are due to government orders. It then declines by about 70% when the mobility measure is estimated in the model. The coefficient on the local incidence of the virus declines significantly with the inclusion of the baseline controls, but has a more modest decline when the government intervention controls are added. In the full model, there is still an economic and statistically significant (p-value of less than .1%) impact of the local incidence of the virus on employment.

Table A2 is analogous to Table A1 but using the CPS data. The national coefficient decreases significantly when adding in government intervention measures, though not as steep of a decline as in Table A1. The coefficient on incidence of COVID-19 has a much steeper decline when adding in demographic controls than observed in the CES data in Table A1. The coefficient maintains statistical significance at the 1% level. The magnitude of the coefficient on incidence increases when the New York City observations are removed, though the standard error also increases, pushing the statistically p-value just outside the range of 5% statistical significance.

Table A1: Impact of Local of Spread of Virus, Current Employment Statistics survey

	Dep. Var: Percent Change in Employment from Previous Month				
Model...	Effect of COVID-19 Cases per 100 in County	Dummy effect of April 2020 (relative to April 2019)	# of Weeks County Shutdown Prior to 4/18	Google Mobility Measure of Retail	Sample Size
...Univariate OLS	-0.13 (0.0021) [<.001]				735725
...OLS w/ Basic Controls	-0.058 (0.0021) [<.001]	-0.083 (0.00084) [<.001]			735725
...OLS w/ Shutdown Measure	-0.051 (0.0021) [<.001]	-0.038 (0.0021) [<.001]	-0.015 (0.00067) [<.001]		735725
...Full OLS Model	-0.043 (0.0022) [<.001]	-0.016 (0.0023) [<.001]	-0.011 (0.00069) [<.001]	0.00082 (4e-05) [<.001]	735725
...Full Model without NYC	-0.048 (0.0026) [<.001]	-0.016 (0.0023) [<.001]	-0.011 (0.0007) [<.001]	0.00082 (4.1e-05) [<.001]	723637

Each row is a separate OLS regressions, with robust standard errors are in parentheses and p-values are in square brackets. Sample includes all establishments with valid responses for the variable in both the response month and previous month from April 2019, February 2020, March 2020, and April 2020. Basic controls are fixed effects for MSA, firm size, industry, whether the establishment is part of a multi-unit firm and population of county. Results are weighted by establishment employment.

Table A2: Impact of Local of Spread of Virus, Current Population Survey

	Dep. Var: Y/N Respondent is on Layoff				
Model...	Effect of COVID-19 Cases per 100 in County	Dummy effect of April 2020 (relative to April 2019)	# of Weeks County Shutdown Prior to 4/18	Google Mobility Measure of Retail	Sample Size
...Univariate OLS	0.15 (0.0069) [<.001]				149291
...OLS w/ Basic Controls	0.024 (0.0058) [<.001]	0.13 (0.0022) [<.001]			149291
...OLS w/ Shutdown Measure	0.021 (0.006) [<.001]	0.093 (0.0043) [<.001]	0.015 (0.0015) [<.001]		149291
...Full OLS Model	0.018 (0.0061) [0.0036]	0.084 (0.0049) [<.001]	0.014 (0.0015) [<.001]	-0.00034 (8.1e-05) [<.001]	149291
...Full Model without NYC	0.023 (0.012) [0.052]	0.083 (0.005) [<.001]	0.014 (0.0015) [<.001]	-0.00034 (8.2e-05) [<.001]	143251

Each row is a separate OLS regressions, with robust standard errors are in parentheses and *p*-values are in square brackets. Sample includes all civilians employed in the previous month from the CPS months April 2019, February 2020, March 2020, and April 2020. Basic controls in the regressions are fixed effects for MSA, gender, age, education, occupation, industry, and population of county. Results are weighted by CPS person weights.

B Additional Figures

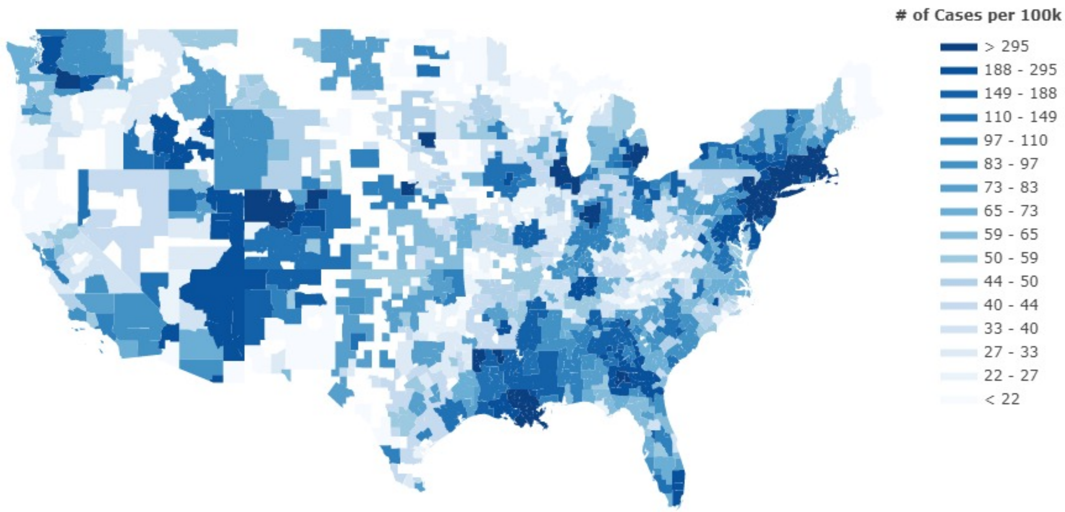

Figure B1: COVID-19 incidence as of April 18th, 2020, total confirmed cases per 100,000 population in county

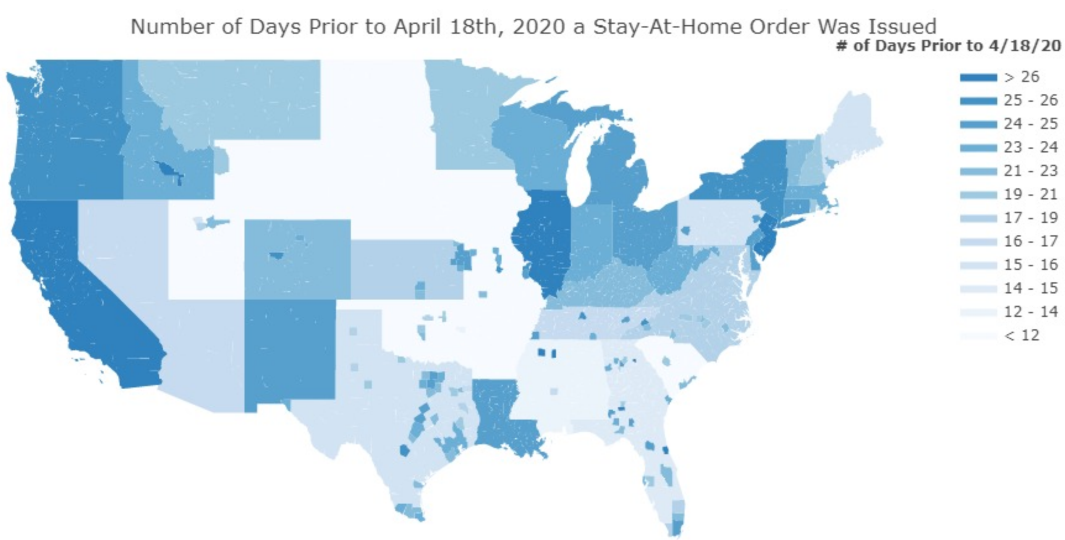

Figure B2: Most variation in stay-at-home orders are at the state level

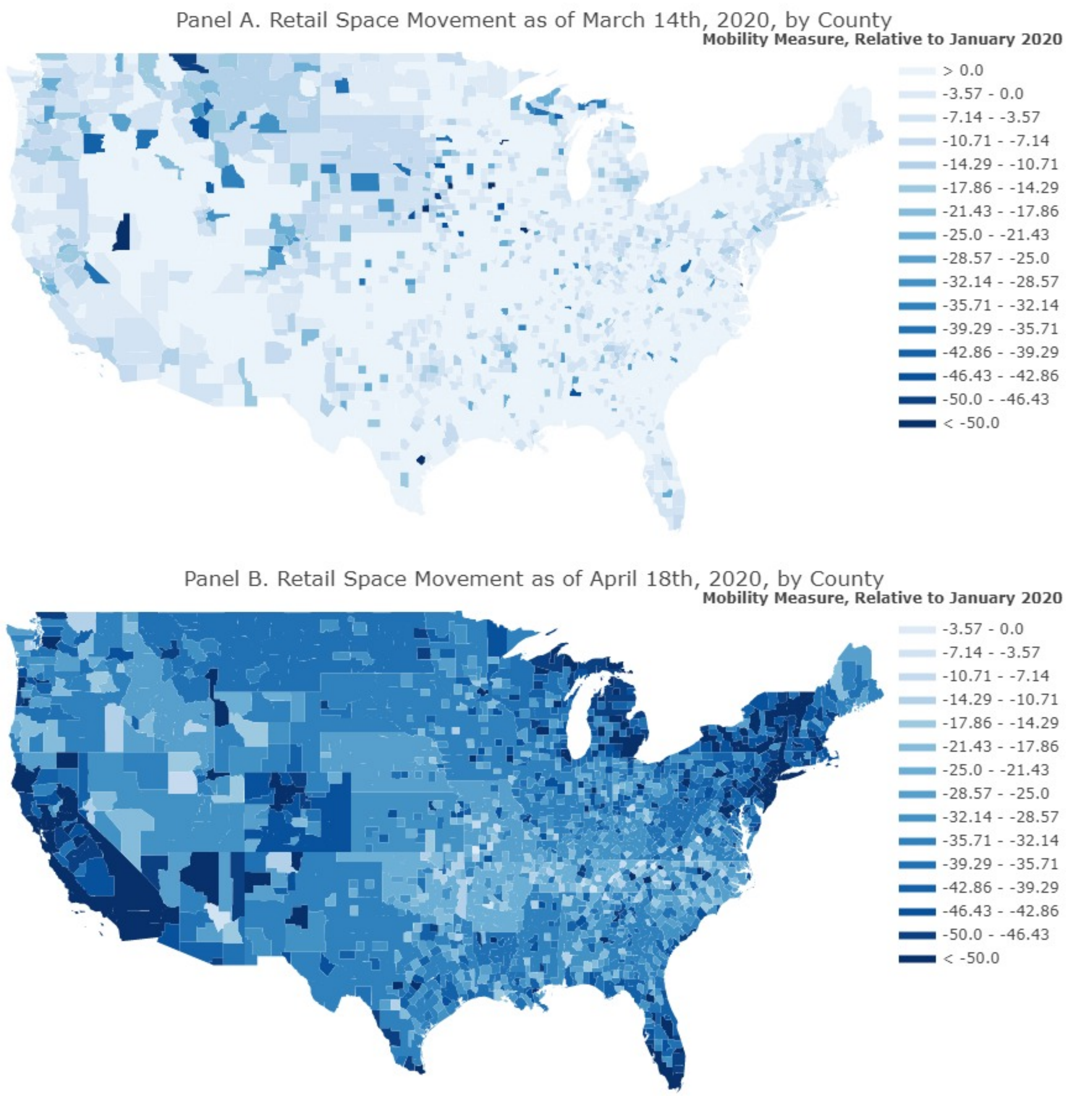

Figure B3: Google mobility data show a steep decline in visits to retail spaces from March to April 2020, relative to the baseline in January 2020

Figure B4: Decline in Employment in April 2020 as COVID-19 Increases, Current Employment Statistics

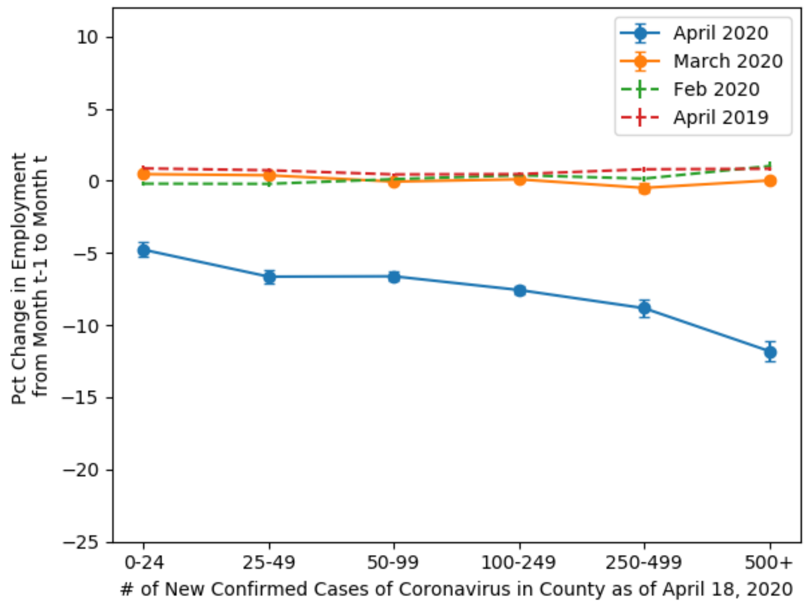

Figure B5: More Workers Leaving Employment as COVID-19 Spreads, Current Population Survey