Employment Impacts of the COVID-19 Pandemic across Metropolitan Status and Size

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Abstract

We examine effects of the COVID-19 pandemic on employment losses across metropolitan area status and population size. Non-metropolitan and metropolitan areas of all sizes experienced significant employment losses, but the impacts are much larger in large metropolitan areas. Employment losses manifest as increased unemployment, labor force withdrawal, and temporary absence from work. We examine the role of individual and local area characteristics in explaining differing employment losses across metropolitan status and size. The local COVID-19 infection rate is a major driver of differences across MSA size. Industry mix and employment density also matter. The pandemic significantly altered urban economic activity.

JEL Codes: J2, R2

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The primary data analyzed in this study are publicly available. The authors will share code and processed data with interested researchers.

1. Introduction

The concentration of economic activity in urban areas has substantial benefits including increased productivity and better consumption opportunities (Glaeser, Kolko, and Saiz 2001; Glaeser and Maré 2001; Lee 2010; Baum-Snow and Pavan 2012; Diamond 2016; Duranton 2016; Bernedo and Patrick 2017; Roca and Puga 2017; Couture and Handbury 2020). However, there are also potential disadvantages of urbanization including longer commutes, higher housing costs, increased income inequality, and decreased happiness (Glaeser, Resseger, and Tobio 2009; Glaeser, Gottlieb, and Ziv 2016; Winters and Li 2017; Combes, Duranton, and Gobillon 2019; Duranton and Puga 2020; Glaeser 2020). The recent and rapid spread of SARS-CoV-2, the novel coronavirus that causes COVID-19, has been especially severe in densely populated urban areas (Desmet and Wacziarg 2020). Concentrating people in small spaces facilitates interactions that are valuable for the spread of knowledge and ideas but also accelerates virus transmission. The COVID-19 pandemic led to massive business closures and reduced economic activity across the globe as governments, firms, and individuals tried to slow the spread of the disease and reduce their own exposure. Unemployment in the United States rose to levels not experienced since the Great Depression (BLS 2020). Many individuals also exited the labor force or became temporarily absent from work, especially in areas with high infection rates (Cho, Lee, and Winters 2020; Cho and Winters 2020; Coibion, Gorodnichenko, and Weber 2020).

In this paper, we examine how the effects of the COVID-19 pandemic on employment changes vary across metropolitan area status and population size. Specifically, we examine differences across non-metropolitans areas and metropolitan areas of increasing size in the U.S. using data from the Current Population Survey. The higher infection rate and greater vulnerability to future infection in more populous metropolitan areas are expected to cause more severe employment losses. Non-metropolitan areas are expected to be less vulnerable than metropolitan areas. Some other factors besides virus transmission may also affect employment losses across metropolitan area status and size including individual characteristics, the industry and occupation mix of local jobs, and the local political environment.

We first document systematic differences in employment rate reductions by metropolitan statistical area (MSA) status and population size. Large employment losses during April and May 2020 were experienced in non-metropolitan areas and MSAs of all sizes, but there are important differences. MSAs with populations greater than five million were hardest hit. Non-metropolitan areas and small metropolitan areas experienced the smallest employment reductions. The unemployment rate regularly understates non-employment (Jones and Riddell 1999; Feng and Hu 2013), and the extent worsened during the COVID-19 pandemic in ways that differ across MSA status and size. Our preferred job loss measure is the change in the percentage of the civilian adult population employed and at work. From April 2019 to April 2020, the employed at work rate fell by 9.6 percentage points in non-metropolitan areas and by 14.6 percentage points in MSAs with more than five people.

We also examine the extent to which the greater employment reductions in large metropolitan areas are due to observable individual and local characteristics. Large MSAs have higher percentages of college graduates and racial and ethnic minorities. College education reduces individual COVID-19 job losses, but Blacks and Hispanics have higher job loss rates than whites (Adams-Prassl et al. 2020; Cho and Winters 2020; Mongey, Pilossoph, and Weinberg 2020). These factors have roughly offsetting effects on differences in employment losses across MSA status and size. Controlling for individual education, race, ethnicity, age, sex, marital status, and children still yields much larger employment losses in large MSAs than in less populous areas. We find that the local COVID-19 infection rate is a major factor explaining differences across MSA size. Industry mix and employment density also appear to be important.

Our paper contributes to the important and rapidly growing research literature on impacts of COVID-19. Previous literature has documented large employment losses (Cajner et al. 2020; Chetty et al. 2020; Cho and Winters 2020). However, the extant literature has not focused on differing employment impacts across metropolitan area status and population size. We make an important empirical contribution for understanding the economic impacts of COVID-19. Unfortunately, the adverse economic impacts are likely to linger, especially if future waves occur, and these effects will be worse for large metropolitan areas. Our paper also has broader implications about the vulnerabilities of urban areas to future viruses and contributes to the research literature on the future of cities and work (Gaspar and Glaeser 1998; Baum-Snow 2013; Glaeser et al. 2018; Autor 2019; Clancy 2020; Delventhal, Kwon, and Parkhomenko, 2020). COVID-19 will not be the last pandemic to afflict the world. Future viruses may pose even greater risks for urban production. Increased efforts to reduce virus exposure and improve local, national, and global resilience will be important.

2. Data

We use individual-level data from the U.S. Current Population Survey (CPS) accessed from IPUMS (Flood et al. 2020). Each month the CPS surveys roughly 60,000 households about their labor market activity, demographics, and other characteristics. The CPS is used by the Bureau of Labor Statistics (BLS) to compute the monthly unemployment rate, labor force participation rate, and related measures for the U.S. Based on responses to multiple CPS questions, the BLS classifies civilians age 16 and over as employed, unemployed, or not in the labor force (BLS 2020). Employed individuals are further separated into those at work during the survey reference week and those with a job but temporarily absent from work.[1] An individual is considered employed and at work if they worked at all for pay or profit during the survey reference week or worked unpaid for at least 15 hours in a family business. Persons who have a job but are temporarily absent include persons on vacation, out sick, or taking a temporary leave of absence; it is not intended to include persons on temporary layoff, but there is some apparent misreporting on this (BLS 2020). An individual is defined as unemployed if they did not work but were willing and able to work and looked for work during the past four weeks or were temporarily laid off. Persons who are neither employed nor unemployed are defined as not in the labor force. The CPS also includes information on individuals' age, education, race, ethnicity, sex, marital status, and presence of own children living in the household.

The CPS includes individuals residing in 260 identifiable metropolitan statistical areas (MSAs). For individuals not living in a metropolitan area, the CPS identifies the state of residence but not the county. A small percentage of individuals in the CPS (4.3 percent for our sample period) live in a small metropolitan area that is not identified or an area that cannot be identified as either metropolitan or non-metropolitan in order to protect individual confidentiality; these observations are necessarily excluded from our analysis. Given the available CPS geographic identifiers, we define local areas as individually identifiable metropolitan statistical areas and state-specific non-metropolitan residuals. Individuals living in metropolitan areas are also classified into the following MSA population size categories: 100,000 – 250,000; 250,000 – 500,000; 500,000 – 1,000,000; 1,000,000 – 2,500,000; 2,500,000

[1]The survey reference week for January through October is the calendar week beginning on a Sunday that includes the 12th of the month. The survey reference week can occur earlier in November and December to avoid overlap with major holidays.

– 5,000,000; and 5,000,000 or larger. We label these as 100-250K, 250-500K, 500K-1M, 1-2.5M, 2.5-5M, and 5M+.

We also obtain data for local area characteristics from other sources. This includes COVID-19 confirmed positive cases by county through April 30, 2020 obtained from USAFacts (2020). We sum the data by local area (individually identifiable MSA or state non-MSA residual) and divide by local area population to compute the percentage of the local population that tested positive by April 30. We also examine COVID-19 deaths per capita as an alternative measure. We obtain 2016 presidential election voting data from the MIT Election Data and Science Lab (2018) and compute the percentage of votes for Trump in each local area. We obtain 2019 total employment in each county from the Quarterly Census of Employment and Wages (QCEW). We use county land area from the U.S. Census Bureau. We compute average employment density in each local area as an employment-weighted average of county-level employment density measured in jobs per square mile.

We also measure local labor market characteristics using data from the 2016-2018 CPS. We use the Dingel and Neiman (2020) measure for which occupations can be done from home to compute the percentage of occupations that can be done remotely for each local area. We construct eight variables measuring the industrial structure in each local area computed as the percentage of local employment in various industries. We discuss more details in the empirical methods section.

3. Empirical Methods

We first investigate changes over time in labor market activity separately for non-metropolitan areas and metropolitan statistical areas (MSAs) of increasing population size. We then conduct regression analysis to assess the importance of individual characteristics and local area characteristics in explaining differing impacts of COVID-19 across MSA status and size.

3.1 Changes over Time by MSA Status and Size

We examine employment activity time trends for non-MSAs and six MSA categories. We highlight 2019-2020 year-over-year changes for each month January through May. We examine rates for unemployment, labor force participation, employment-to-population, having a job but not at work, and employed at work. The unemployment rate is computed as a percentage of the labor force. The other rates are computed as a percentage of the civilian adult population. All of our analysis uses CPS survey weights. We view the employed at work rate as the preferred comprehensive measure because it accounts for changes in unemployment, labor force participation, and temporary absence from work. The COVID-19 pandemic is expected to significantly decrease employment activity in April and May 2020 relative to the same month the previous year. March 2020 is expected to be partially impacted, but employment measures in January and February 2020 are not expected to be affected by COVID-19.

We also estimate difference-in-differences (DD) coefficients intended to account for the moderately stronger economic conditions at the start of 2020 compared to 2019. Specifically, we define April 2020 and May 2020 as treated by COVID-19 but define January 2020 and February 2020 as untreated. Since March 2020 was likely partially treated, we exclude it from the DD analysis. We construct the DD estimates as the April-May year-over-year change minus the January-February year-over-year change. This assumes that the counterfactual year-over-change for April-May in the absence of COVID-19 would equal the year-over-year change for January-February. Similar DD approaches are used in Cho and Winters (2020) and Cho, Lee, and

Winters (2020). The DD coefficient is estimated separately for non-metropolitan areas and for each MSA size group.

3.2 Accounting for Individual and Local Area Characteristics

We estimate linear probability models to assess the importance of individual and local area characteristics for explaining differences in employment impacts across MSA status and size. Specifically, we estimate the following difference-in-differences-in-difference (DDD) regression models:

$$Y_{iat} = \gamma MSAGroup_a \times APRMAY2020_t + \Theta Area_a + \Pi Area_a \times APRMAY_t + \Phi Area_a \times 2020_t + \alpha APRMAY2020_t + \varepsilon_{iat} \quad (1)$$

$$Y_{iat} = \gamma MSAGroup_a \times APRMAY2020_t + \Theta Area_a + \Pi Area_a \times APRMAY_t + \Phi Area_a \times 2020_t + \beta X_{iat} \times TIME_t + \varepsilon_{iat} \quad (2)$$

$$Y_{iat} = \gamma MSAGroup_a \times APRMAY2020_t + \Theta Area_a + \Pi Area_a \times APRMAY_t + \Phi Area_a \times 2020_t + \beta X_{iat} \times TIME_t + \delta Z_a \times APRMAY2020_t + \varepsilon_{iat} \quad (3)$$

The dependent variable, Y_{iat}, is a binary employment status indicator for individual i living in local area a and observed in time period t. To facilitate comparison with the aggregate employment rate, we code the dependent variable as either zero or 100 instead of zero or one. Each local area is either an individually identifiable metropolitan area or a state-specific non-metropolitan residual. $MSAGroup_a$ is a set of indicators for six MSA size groups listed in the data section. Non-metropolitan areas are the omitted reference group. $APRMAY2020_t$ is an indicator equal to one for April-May 2020, the COVID-19 treatment period; it equals zero for other time periods. $MSAGroup_a \times APRMAY2020_t$ is a set of interaction variables representing MSA group specific indicators for the COVID-19 treatment period. $Area_a$ is a set of indicator variables for each local area. $APRMAY_t$ is an indicator equal to one for April-May and zero for January-February. 2020_t is an indicator equal to one for 2020 and zero for 2019. Thus, $Area_a \times APRMAY_t$ and $Area_a \times 2020_t$ are time-specific indicators for each local area, but we do not include a full set of area-by-time indicators because doing so would prevent identification of $MSAGroup_a \times APRMAY2020_t$ due to perfect collinearity. $X_{iamt} \times TIME_t$ is a set of individual characteristics interacted with a full set of time (month-year) dummies. $Z_a \times APRMAY2020_t$ is a set of local area characteristic variables interacted with the indicator for the treatment period. ε_{iamt} is a mean zero error term. We cluster standard errors by local area.

We are estimating DDD models because we are taking differences across calendar months, years, and local areas relative to non-metropolitan areas. Equation (1) is equivalent to computing a simple difference-in-differences coefficient for each local area and then estimating a weighted regression of these DD coefficients on MSA group indicators with weights equal to the sum of individual weights by local area. Thus, we are comparing how the COVID-19 treatment effect differs between each MSA size group and non-metropolitan areas. Equation (1) is also similar to the DD analysis in section 3.1, but instead of estimating separate DD coefficients for non-metropolitan areas and each MSA size group, we are now estimating the effects jointly and relative to the effect for non-MSAs.[2]

Equation (2) modifies equation (1) by adding detailed control variables for individual characteristics interacted with time. These interactions are collinear with the $APRMAY2020_t$ variable from equation (1), so it is excluded from equation (2). The individual characteristics include dummy variables for single year of age, sex, race, ethnicity, education, marital status,

[2] The two approaches also differ in how weights are applied, but these are very similar calculations and produce very similar results.

and presence of children in the household. Equation (2) helps assess the extent to which differences in COVID-19 impacts across MSA status and size are explained by individual characteristics.

Equation (3) further adds explanatory variables for local area characteristics interacted with the $APRMAY2020_t$ indicator. The local area characteristics include the log of the COVID-19 infection rate, the percentage of 2016 presidential election votes for Trump, the percentage of occupations in 2016-2018 that could be done from home, eight industrial structure variables measuring the percentage of 2016-2018 employment in specific industries, and the log of local area average employment density. Equation (3) is useful for assessing the extent to which differences across MSA status and size are due to these local area characteristics. The impacts of the characteristics are also of direct interest themselves.

We expect the local infection rate to have a significant adverse effect on employment due to efforts to reduce spread and exposure (Chetty et al. 2020). We expect areas with higher vote shares for Trump to have better employment outcomes during April-May 2020 because of less concern about the virus and reduced compliance with social distancing guidelines (Barrios and Hochberg 2020). A higher percentage of occupations that can be done from home is expected to produce better employment outcomes in April-May 2020 (Dingel and Neiman 2020).

The industrial structure variables include the percentages of employment in 1) construction; 2) transportation and utilities; 3) wholesale and retail trade; 4) professional, business, information, and financial services; 5) education and health services; 6) leisure and hospitality; 7) other services; and 8) public administration. The omitted industry group includes agriculture, mining, and manufacturing. We intentionally construct the omitted group to include primary and secondary industries that form the economic base for many areas. We do not separate out agriculture or mining because they are overwhelmingly concentrated in non-metropolitan areas and small metropolitan areas and would likely capture effects beyond the direct effect of industrial composition. We expect prior employment concentration in leisure and hospitality to have a negative effect on employment outcomes during the COVID-19 treatment period. We also expect areas with more employment in transportation and utilities and public administration to have better employment outcomes during April-May 2020. Expectations for the other industry variables are more ambiguous.

We expect employment density to have an adverse effect on April-May 2020 employment outcomes because of greater vulnerability to future COVID-19 infection even after controlling for COVID-19 confirmed infections. We estimate equation (3) with and without the employment density variable for two main reasons. First, employment density is intrinsically linked to MSA status and size in ways that may complicate interpreting the results for other variables. Second, density is imperfectly measured and imperfectly matched to individuals. Our measure uses an employment-weighted average of county employment density, but there are notable variations in employment density within counties, and we do not have employment density at finer geographic levels. Furthermore, CPS geographic identifiers are based on where individuals live and not where they work, so there would be some mismatch even with sub-county data on employment density. We cannot account for cross-area commuting, e.g., many workers live in non-metropolitan areas but commute to a nearby metropolitan area for employment. Mismeasurement may be especially pronounced for non-metropolitan area residents. Thus, we expect our employment density variable to be a good but imperfect measure.

4. Empirical Results

4.1 Changes over Time by MSA Status and Size

Figure 1 illustrates the monthly unemployment rate, labor force participation rate, and employed at work rate for January 2019 through May 2020 for non-metropolitan areas and for MSAs with population 100-250K, 250-500K, 500K-1M, 1-2.5M, 2.5-5M, and 5M+.

The unemployment rate was relatively flat overall and similar for each group from January 2019 to February 2020. However, the unemployment rate began increasing in March 2020 and exceeded 13 percent for every group in April 2020. The April 2020 unemployment rate was highest for the three largest MSA population groups and lowest for non-MSAs and the smallest MSA population group. The unemployment rate decreased some in May 2020 as businesses began reopening, but the recovery for the very largest MSA group was only slight. The May 2020 unemployment rate for MSAs with population 5M+ was 15.1 percent, while the rates for non-MSAs and the smallest MSAs were roughly 10.6 percent. Thus, unemployment effects of COVID-19 were larger for very large MSAs than for less populous areas.

The labor force participation rate exhibits notable differences across groups even before COVID-19 hit the U.S. Non-MSAs have the lowest participation rate in every month considered, and the three largest MSA population groups had the highest labor force participation rates. These persistent differences in labor force participation between large and small labor markets may reflect some combination of local differences in labor demand, matching, age structure, and cultural norms. Additionally, labor force participation decreased for all groups in April 2020 and despite some recovery remained below pre-pandemic levels in May 2020 for most groups.

The employed at work rate is lowest for non-MSAs throughout the entire period similar to the labor force participation rate. The three largest MSA population groups had the highest employed at work rates for January 2019 through February 2020, again consistent with the labor force participation rate. All groups experienced declines in employed at work rates during April 2020 and some recovery in May 2020. The largest MSA population groups experienced the largest declines in employed at work rates.

Table 1 reports 2019-2020 year-over-year changes for January – May and the simple difference-in-difference estimates. Column (1) includes results for non-metropolitan areas. Columns (2) through (7) include results for MSAs with population 100-250K, 250-500K, 500K-1M, 1-2.5M, 2.5-5M, and 5M+. Panel A examines the unemployment rate. Panels B, C and D examine the labor force participation rate, employment-to-population ratio, and has job not at work rate. Panel E reports changes in the employed at work rate.

Panel A indicates large April and May year-over-year increases in unemployment for non-MSAs and every MSA group. However, the differences across groups are striking. Between May 2019 and May 2020, the unemployment rate increased by 6.9 and 7.0 percentage points in non-MSAs and MSAs with population 100-250K. However, the increase in unemployment typically increases with MSA population, and MSAs with population 5M+ experienced an 11.5 percentage point increase in the unemployment rate from May 2019 to May 2020. Similarly, the unemployment rate DD estimates are large for every group but range from 8.1 for non-MSAs to 12.0 for MSAs with population 5M+. Larger labor markets are much more severely impacted by the COVID-19 shock to U.S. labor markets.

Panel B reports significant April and May year-over-year decreases in labor force participation rates for most groups, with the largest DD magnitudes for the largest population MSAs. Panel C reports considerable decreases in the employment-population ratio with DD estimates that are again largest for large population MSAs. Panel D documents that every group experienced increases in the has job not at work rate and the increase was largest for MSAs with population 5M+, though the magnitude is otherwise not systematic across MSA population.

Panel E indicates significant April and May year-over-year decreases in the employed at work rate for every group. Recall that changes in the employed at work rate incorporate changes in unemployment, labor force participation, and having a job but being temporarily absent from work. We view changes in employed at work rates as the single best comprehensive measure for assessing job losses due to COVID-19. The May 2019 to May 2020 decrease was 6.1 percentage points for non-MSAs but 11.6 percentage points for the largest MSA group. Similarly the employed at work DD estimate in Panel E is -8.4 for non-MSAs and -14.1 for MSAs with population 5M+. The largest labor markets suffered the largest employment decreases from COVID-19.

Our main analysis includes civilians ages 16 and older, but there is some interest in examining a narrower age range with stronger labor market ties. Therefore, we replicated Table 1 restricting the sample to ages 25-61; results are in Appendix Table A1. The results are qualitatively similar, but magnitudes are often larger because the narrower sample has higher baseline employment rates. For example, the employed at work analysis in Panel E indicates DD estimates of -9.2 for non-MSAs and -16.4 for MSAs with population 5M+. Thus, COVID-19 generally decreases the employed at work rate even more for ages 25-61 and the difference between non-MSAs and large MSAs becomes even larger.

There is also interest in how individual metropolitan areas were affected. CPS sample sizes are not very large for smaller MSAs, which prevents precise estimates. However, sample sizes are sufficient for reasonably precise estimates for larger MSAs. Appendix Table A2 reports employed at work rate year-over-year changes for April and May and DD estimates for the 50 largest population MSAs. According to the DD estimates, Las Vegas was the hardest hit among the 50 largest MSAs followed by Detroit and Orlando. Las Vegas and Orlando were hard hit because of their reliance on leisure and hospitality industries, while Detroit is heavily reliant on automobile manufacturing and related industries. Finally, the five lowest DD estimates among the 50 largest MSAs were all for MSAs with populations of less than 1.5 million.

4.2 Accounting for Individual and Local Area Characteristics

We next consider the importance of individual and local characteristics for the differing impacts of COVID-19 on employed at work rates across MSA status and size. Before proceeding to DDD estimates for equations (1) – (3), we first present sub-sample means for selected explanatory variables in Table 2. Individual characteristics and local area characteristics vary across MSA status and size in important ways. Non-MSAs are the oldest and mean age decreases with MSA population. The percentage female does not systematically vary. The percentages of Hispanics, Blacks, and Asians increase with MSA status and size. Bachelor's degree attainment rates increase with MSA status and size. The percentage married decreases with MSA status and size, but the percentage with kids in the household increases. The infection rate variable is measured in logs, so the means are negative for all groups, but the mean increases (becomes less negative) with MSA size. The percentage of votes for Trump decreases with MSA status and size. The percentage of occupations that can be done from home increases with MSA status and size. The industrial structure varies some, but the differences are often relatively small and not systematic. The most systematic difference in industrial structure is that the percentage in professional, business, information, and financial services (collectively referred to as professional services) increases significantly with MSA status and size. While not explicit in the table, the share of the omitted group that includes agriculture, mining, and manufacturing systematically decreases with MSA status and size. Log average employment density increases with MSA status and size.

Table 3 presents DDD results for changes in employed at work. Columns (1) and (2) present results for equations (1) and (2). Columns (3) and (4) present results for equation (3) without and with the employment density variable.

Column (1) of Table 3 excludes individual and local characteristic variables. The $APRMAY2020$ indicator variable measures the effect of COVID-19 for non-MSAs and the interactions of MSA size indicators with $APRMAY2020$ measure effects of COVID-19 relative to non-MSAs. The coefficient estimate for $APRMAY2020$ indicates that COVID-19 decreased the employed at work rate in non-metropolitan areas in April-May 2020 by 8.4 percentage points, a virtually identical estimate as the corresponding DD estimate in Table 1. The coefficient estimates for interactions of $APRMAY2020$ with MSA size dummies in Column (1) are all negative and statistically significant for the four largest population groups. The Column (1) coefficient estimates also increase with MSA population. The coefficient for the largest MSA group implies that COVID-19 decreased employed at work by 5.6 percentage points more in MSAs with population 5M+ than in non-MSAs, an estimate that is also nearly identical to that implied by Table 1.

Column (2) of Table 3 includes controls for interactions of individual characteristics and time dummies. Coefficient estimates in Column (2) are again all negative and statistically significant for the four largest MSA population groups. Coefficient estimates for the four smallest MSA population groups all decrease somewhat. Thus, differences in individual characteristics appear to explain some of the differences between non-MSAs and small and medium population MSAs. However, the coefficient estimate for MSAs 2.5-5M increases slightly and the coefficient estimate for MSAs 5M+ decreases only slightly indicating that individual characteristics do not explain the differences in COVID-19 employment impacts between non-MSAs and large MSAs.[3]

Columns (3) and (4) include the individual controls and add interactions of local area characteristics with the $APRMAY2020$ indicator. Our DDD approach is similar to estimating a DD coefficient for each local area and then estimating a weighted regression of the DD coefficients on MSA size indicators and local area characteristics. The main difference is that our DDD approach is done via a single regression and includes individual controls. Adding the local characteristic variables substantially alters the coefficient estimates for the MSA size interactions with $APRMAY2020$. In Column (3) the MSA size interactions with $APRMAY2020$ coefficient estimates are now positive for the four smallest groups, but relatively small in magnitude and not statistically significant. The coefficient estimates for the two largest MSA size groups are still negative but greatly reduced in magnitude and no longer statistically significant. In particular, the coefficient estimate for MSAs with population 5M+ decreases from -5.6 in Column (1) to -1.3 in Column (3) indicating that the variables in Column (3) collectively explain 76 percent of the differing impact of COVID-19 between non-MSAs and MSAs with population 5M+. Similarly, we cannot reject the hypothesis of equal impacts of COVID-19 on non-MSAs and the largest MSAs after controlling for the variables in Column (3).

[3] Appendix Table A3 examines separate impacts of subsets of individual controls. Age, gender, marital status, and presence of children explain little of the differences between non-MSAs and the two largest MSA groups. However, controlling only for race and ethnicity decreases the coefficient estimates for large MSAs while controlling only for education increases these coefficient estimates. The net effect is that controlling for the full set of individual characteristics explains virtually none of the difference between non-MSAs and the two largest MSA groups.

Adding the employment density variable in Column (4) yields positive coefficient estimates for all of the MSA size interactions with $APRMAY2020$, and three of the smallest four groups are significant at the five percent level; the second smallest MSA group coefficient is also significant at the 10 percent level. The coefficient estimates for the two largest groups are not significant, but the contrast with Column (1) is again notable. However, we reiterate our earlier discussion that density is imperfectly measured, especially for non-MSAs. Because the density variable has a negative coefficient in Column (4) and the density variable means differ substantially across MSA status and size, measurement error may have an unintended influence on the coefficients for the MSA size interactions with $APRMAY2020$. Specifically, if employment density in non-MSAs is disproportionately under-measured, it would induce a positive bias in the coefficients for the MSA size interactions with $APRMAY2020$.

The COVID-19 infection rate variable has a large and statistically significant negative effect on employment in both Columns (3) and (4). In fact, the infection variable is the single most important factor in Column (3) for explaining differences across MSA status and size. Multiplying the coefficient (-2.184) by the difference in the infection variable means between non-MSAs and the largest MSA group (1.39) indicates that the infection variable explains 54 percent of the 5.6 percentage point gap in Column 1. The decreased coefficient of -1.888 in Column (4) still explains 47 percent of the 5.6 percentage point difference in Column 1. Thus, the higher infection rate in very large MSAs explains roughly half of the larger employment decreases relative to non-MSAs. If we compare the largest MSA group to the smallest MSA group, the percentage difference in employment losses explained by the infection variable is slightly higher because the infection rate was even lower in the smallest MSA group than in non-MSAs and the initial difference in Column 1 is somewhat smaller.

The variable for the percentage voting for Trump has a small coefficient that is not statistically significant for both Columns (3) and (4). The work from home variable has a positive coefficient estimate in both columns, but the estimates are not significant. However, we include detailed individual controls and additional industry controls. Ability to work from home certainly matters for individuals, but the MSA percentage is not significant in our models. Only two of the industrial structure variables are statistically significant. The percentage employed in transportation and utilities has a positive coefficient estimate in both columns as expected. The percentage employed in leisure and hospitality has a negative coefficient in both columns as expected. However, neither of these two industry variables differ systematically across MSA status and size in Table 2, and they do not explain much of the differences in employment impacts across MSA status and size. The industry variable that differs most systematically in Table 2 is the percentage employed in professional services, and this variable has a negative but not significant coefficient in both Columns (3) and (4) of Table 3.

The density variable has a significant negative coefficient of -0.714 in Column (4). Multiplying the coefficient by the Table 2 mean difference between non-MSAs and the largest MSAs (6.85) implies that the density variable explains 87 percent of the 5.6 percentage point difference in Column 1 of Table 3. The density variable is imperfectly measured, but the magnitude implied is substantial and suggestive of an important effect. Similar calculations imply that the density variable explains 54 percent of the Column 1 employment difference between MSAs with population 5M+ and MSAs with population 100-250K. Thus, density appears to have a large and important adverse effect on employment during the COVID-19 pandemic even independent of the observed infection rate. This may reflect heightened concerns about future infections in dense areas and reduced economic activity in response.

Appendix Table A4 estimates separate DDD effects for April 2020 and May 2020 corresponding to Columns (1) and (4) of Table 3. The $APRMAY2020$ coefficient is smaller for May than April, but the other variable coefficients are overall largely similar for April and May. Appendix Table A5 reports alternative models using COVID-19 death rates corresponding to Columns (3) and (4) of Table 3. The death rate coefficients are significantly negative though moderately smaller magnitude than the main infection variable. However, death rates are also less dispersed across MSA status and size. Multiplying the coefficients by variable mean differences across groups, the alternative COVID-19 variables explain 38-53 percent of the employment loss differences between non-MSAs and the largest MSA group.

Finally, our analysis does not include state policy variables measuring restrictions on economic activity and individual mobility. The policies are numerous, overlapping, inconsistently enforced, difficult to accurately measure, and driven by other factors (e.g. infections and politics) including some that are difficult to measure (e.g. leadership) making causal inference difficult (Goodman-Bacon and Marcus 2020). Monthly CPS data are also not ideal for analyzing policies that change by day and week. To gauge the potential impact of state policies on our analysis, Appendix Table A6 reports DDD regression results similar to Table 3 but include indicator variables for interactions of state and month-year to control for state×time effects. Thus, identifying variation is now restricted to differences across local areas within a state in a given month-year and not driven by state policies. State×time effects absorb considerable variation and reduce estimate precision. State×time effects may also increase measurement error attenuation bias for local area characteristic variables, so this is not our preferred specification. The results in Appendix Table A6 are largely similar to Table 3. The Column (1) coefficient for MSAs with population 5M+ is -4.86, which is similar to the Table 3 coefficient of -5.64 and indicates that the large difference between non-MSAs and the largest MSA group is not driven by state policy differences. Furthermore, the infection variable continues to have a large and significant negative effect on employment in Columns (3) and (4) and explains 44-49 percent of the differing employment impact between non-MSAs and MSAs with population 5M+.

5. Conclusion

COVID-19 severely disrupted labor markets in areas big and small. However, employment rate decreases in the United States during April-May 2020 increase with metropolitan statistical area status and population size. Difference-in-differences estimates indicate that employed at work rates decreased by 8.4 percentage points in non-metropolitan areas but by 14.1 percentage points in MSAs with populations greater than five million. We use a difference-in-differences-in-differences regression analysis to examine the importance of individual and local area characteristics. Controlling for the full set of individual characteristics does not meaningfully explain the differing employment impacts between non-MSAs and MSAs with populations greater than five million. Local area characteristics are important. The local infection rate explains roughly half of the differing employment changes between non-MSAs and the largest MSAs. Employment density also appears to be important even controlling for confirmed infection rates, possibly suggesting that density amplifies COVID-19 concerns above and beyond confirmed infection rates.

COVID-19 has had devastating effects on health, productivity, and well-being. Large and densely populated urban areas are especially vulnerable to and impacted by COVID-19. Future viruses may pose even greater risks. Urban areas may become less attractive places to live and work (Bender 2020). There is a clear need for policy and business leaders to work to mitigate vulnerabilities to COVID-19 and future viruses. Increased social distancing, mask wearing, and testing are unpleasant to many but likely warranted in the near term and perhaps well into the future. Increased working from home may also persist even after the current pandemic subsides. The structure of intra-national and international trade may change forever. National populations may become less concentrated in large cities as people and firms move away. There is still much uncertainty, but it is clear that COVID-19 has and will continue to alter urban economic activity.

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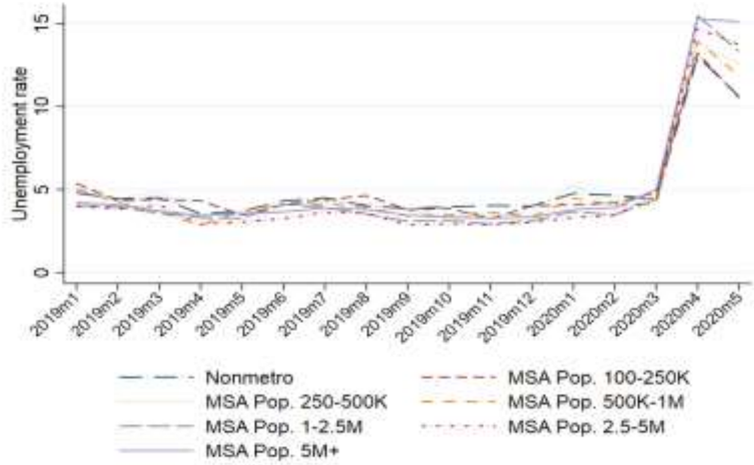
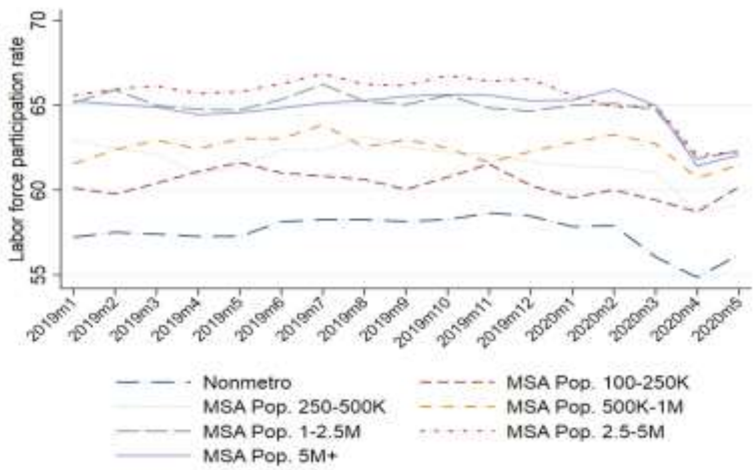
Figure 1: Unemployment, Labor Force Participation, and Employed at Work Rates

a) Unemployment Rate



b) Labor Force Participation Rate



c) Employed at Work Rate

Table 1: COVID-19 Labor Market Impacts by MSA Status and Size

	(1) Non-Metro	(2) MSA Pop. 100-250K	(3) MSA Pop. 250-500K	(4) MSA Pop. 500K-1M	(5) MSA Pop. 1-2.5M	(6) MSA Pop. 2.5-5M	(7) MSA Pop. 5M+
A. Unemployment Rate							
May 2020 - May 2019	6.901**	7.062**	9.755**	8.156**	10.049**	10.682**	11.559**
Apr. 2020 - Apr. 2019	9.498**	8.912**	10.627**	11.077**	12.168**	11.784**	11.873**
Mar. 2020 - Mar. 2019	-0.092	0.422	-0.353	0.501	0.814*	0.576	1.277**
Feb. 2020 - Feb. 2019	0.201	-0.118	-0.684	-0.194	-0.469	-0.375	-0.138
Jan. 2020 - Jan. 2019	-0.026	-1.288*	0.233	-0.537	-0.387	-0.686*	-0.432
Diff.-in-Diff.	8.096**	8.664**	10.416**	9.973**	11.531**	11.763**	12.000**
DD St. Error	(0.455)	(0.663)	(0.612)	(0.475)	(0.426)	(0.457)	(0.382)
B. Labor Force Participation Rate							
May 2020 - May 2019	-1.083	-1.451	-2.269*	-1.560*	-2.399**	-3.560**	-2.500**
Apr. 2020 - Apr. 2019	-2.423**	-2.379*	-2.274*	-1.717*	-2.929**	-3.630**	-3.025**
Mar. 2020 - Mar. 2019	-1.341*	-0.982	-1.081	-0.203	-0.258	-1.123	0.089
Feb. 2020 - Feb. 2019	0.386	0.247	-1.137	0.906	-0.804	-1.078	0.887
Jan. 2020 - Jan. 2019	0.621	-0.571	-1.540	1.272	-0.148	0.024	0.052
Diff.-in-Diff.	-2.257**	-1.748	-0.930	-2.727**	-2.187**	-3.065**	-3.232**
DD St. Error	(0.662)	(0.987)	(0.897)	(0.695)	(0.630)	(0.690)	(0.551)
C. Employment-to-Population Ratio							
May 2020 - May 2019	-4.921**	-5.650**	-7.973**	-6.516**	-8.584**	-10.101**	-9.587**
Apr. 2020 - Apr. 2019	-7.547**	-7.509**	-8.435**	-8.393**	-10.357**	-10.838**	-10.214**
Mar. 2020 - Mar. 2019	-1.229	-1.189	-0.812	-0.510	-0.776	-1.452*	-0.744
Feb. 2020 - Feb. 2019	0.252	0.307	-0.668	0.990	-0.467	-0.793	0.942
Jan. 2020 - Jan. 2019	0.607	0.227	-1.604	1.545*	0.110	0.474	0.332
Diff.-in-Diff.	-6.663**	-6.835**	-7.066**	-8.723**	-9.290**	-10.307**	-10.538**
DD St. Error	(0.667)	(1.003)	(0.911)	(0.709)	(0.644)	(0.705)	(0.564)
D. Has Job Not at Work Rate							
May 2020 - May 2019	1.178**	1.809**	1.611**	1.492**	1.500**	1.158**	1.975**
Apr. 2020 - Apr. 2019	2.094**	2.917**	3.050**	2.702**	2.246**	1.859**	4.396**
Mar. 2020 - Mar. 2019	0.109	0.433	0.367	0.193	0.819**	0.625**	0.598**
Feb. 2020 - Feb. 2019	0.069	0.424	-0.357	-0.105	0.117	-0.319	-0.344*
Jan. 2020 - Jan. 2019	-0.336*	0.110	-0.444	-0.291	0.123	-0.371	-0.326*
Diff.-in-Diff.	1.770**	2.097**	2.727**	2.294**	1.752**	1.854**	3.521**
DD St. Error	(0.197)	(0.306)	(0.285)	(0.219)	(0.195)	(0.216)	(0.183)
E. Employed at Work Rate							
May 2020 - May 2019	-6.099**	-7.460**	-9.584**	-8.008**	-10.084**	-11.259**	-11.562**
Apr. 2020 - Apr. 2019	-9.641**	-10.426**	-11.485**	-11.095**	-12.603**	-12.698**	-14.610**
Mar. 2020 - Mar. 2019	-1.338*	-1.622	-1.179	-0.703	-1.595*	-2.076**	-1.342*
Feb. 2020 - Feb. 2019	0.183	-0.117	-0.311	1.095	-0.585	-0.474	1.287*
Jan. 2020 - Jan. 2019	0.942	0.117	-1.161	1.837**	-0.014	0.844	0.658
Diff.-in-Diff.	-8.433**	-8.931**	-9.793**	-11.017**	-11.042**	-12.160**	-14.059**
DD St. Error	(0.669)	(1.007)	(0.916)	(0.713)	(0.649)	(0.711)	(0.568)

Notes: The full sample includes civilians age 16 and over. The Diff.-in-Diff is computed via linear regression and measures an average effect for April-May 2020 relative to 2019 and January-February.
*Significantly different from zero at 5% level; ** Significant at 1% level.

Table 2: Sub-Sample Means for Selected Explanatory Variables by MSA Status and Size

	(1) Non-Metro	(2) MSA Pop. 100-250K	(3) MSA Pop. 250-500K	(4) MSA Pop. 500K-1M	(5) MSA Pop. 1-2.5M	(6) MSA Pop. 2.5-5M	(7) MSA Pop. 5M+
Individual Characteristics							
Age	49.27	47.68	47.21	47.01	46.05	45.86	45.63
Female	0.511	0.521	0.519	0.518	0.520	0.513	0.516
Hispanic	0.063	0.110	0.158	0.172	0.134	0.175	0.266
Black	0.079	0.099	0.110	0.099	0.134	0.103	0.167
Asian	0.009	0.025	0.032	0.045	0.063	0.093	0.100
Native American	0.019	0.009	0.005	0.008	0.005	0.006	0.002
Hawaiian/Pacific Islander	0.002	0.003	0.002	0.005	0.003	0.004	0.002
Two or more races	0.014	0.018	0.016	0.019	0.018	0.017	0.010
High School Diploma	0.363	0.302	0.291	0.284	0.258	0.234	0.236
Some College	0.291	0.298	0.291	0.276	0.272	0.267	0.232
Bachelor's Degree or Higher	0.199	0.270	0.288	0.311	0.357	0.384	0.388
Married	0.533	0.519	0.515	0.514	0.507	0.505	0.496
Has Kids in Household	0.317	0.335	0.344	0.348	0.355	0.355	0.381
Local Area Characteristics							
Ln COVID-19 Rate by Apr. 30	-2.27	-2.35	-2.19	-2.02	-1.91	-1.62	-0.87
% Voted Trump 2016	63.03	55.90	50.56	47.65	44.73	37.84	35.57
% Occ. Can Work from Home	29.07	34.40	35.83	38.45	42.11	44.98	43.86
% Employed in Construction	7.40	6.75	6.88	7.19	6.85	6.63	7.09
% Emp. Wholesale/Retail	13.38	13.86	13.66	13.86	13.21	12.82	12.84
% Emp. Transport./Utilities	5.38	4.58	4.70	4.76	5.32	5.14	6.26
% Emp. Professional Services	11.87	15.19	17.18	19.55	22.56	25.17	25.29
% Emp. Education/Health	23.08	24.84	23.58	23.49	22.06	21.87	21.56
% Emp. Leisure/Hospitality	8.03	9.71	9.94	9.27	10.23	9.27	9.24
% Emp. Other Services	4.59	4.76	5.15	4.82	4.68	4.76	5.30
% Emp. Public Admin.	5.33	5.29	4.81	4.74	4.54	4.31	4.21
Ln Average Emp. Density	1.17	4.42	4.99	5.53	6.49	6.75	8.03

Notes: The full sample includes 683,753 individuals age 16 and over. The COVID-19 variable is the natural log of the percentage of the local population that had tested positive by April 30, 2020. Average employment density is an employment-weighted average of county-level employment density measured in jobs per square mile; we then take the natural log.

Table 3: Employed at Work DDD Results without and with Individual and Local Area Controls

	(1)	(2)	(3)	(4)
MSA Pop. 100-250K × AprMay2020	-0.864	-0.370	0.725	2.859*
	(1.294)	(0.977)	(1.127)	(1.268)
MSA Pop. 250-500K × AprMay2020	-1.601	-0.594	1.109	3.547
	(1.691)	(1.574)	(1.601)	(1.869)
MSA Pop. 500K-1M × AprMay2020	-2.516*	-1.385*	0.506	3.093*
	(0.975)	(0.680)	(0.945)	(1.345)
MSA Pop. 1-2.5M × AprMay2020	-2.651**	-1.951*	0.901	3.963*
	(0.883)	(0.753)	(1.233)	(1.592)
MSA Pop. 2.5-5M × AprMay2020	-3.742**	-3.989**	-0.691	2.262
	(0.847)	(0.678)	(1.260)	(1.614)
MSA Pop. 5M+ × AprMay2020	-5.637**	-5.500**	-1.329	2.363
	(0.880)	(0.741)	(1.468)	(1.991)
AprMay2020	-8.381**			
	(0.671)			
Ln COVID Case Rate by April 30 × AprMay2020			-2.184**	-1.888**
			(0.340)	(0.348)
% Voted Trump 2016 × AprMay2020			0.002	0.006
			(0.032)	(0.033)
% Occ. Can Work from Home × AprMay2020			0.076	0.076
			(0.087)	(0.087)
% Employed in Construction × AprMay2020			0.269	0.246
			(0.165)	(0.165)
% Emp. Wholesale/Retail × AprMay2020			0.009	-0.043
			(0.147)	(0.147)
% Emp. Transportation/Utilities × AprMay2020			0.495*	0.507*
			(0.205)	(0.206)
% Emp. Professional Services × AprMay2020			-0.133	-0.061
			(0.103)	(0.105)
% Emp. Education/Health × AprMay2020			0.118	0.162
			(0.106)	(0.108)
% Emp. Leisure/Hospitality × AprMay2020			-0.548**	-0.578**
			(0.111)	(0.111)
% Emp. Other Services × AprMay2020			0.471	0.405
			(0.308)	(0.308)
% Emp. Public Administration × AprMay2020			0.188	0.154
			(0.126)	(0.127)
Ln Average Emp. Density × AprMay2020				-0.714*
				(0.281)
Individual Characteristics × Time Dummies	No	Yes	Yes	Yes

Notes: The sample includes civilians age 16 and over. Standard errors in parentheses are clustered by local area. Local areas include individual MSAs and state-specific non-MSA residual areas. Non-MSAs are the excluded MSA status/size group. Regressions also include local area fixed effects, area×2020 effects, and area×AprMay effects.

*Significantly different from zero at 5% level; ** Significant at 1% level.

Appendix Tables

Table A1: COVID-19 Labor Market Impacts by MSA Status and Size for Ages 25-61

	(1) Non-Metro	(2) MSA Pop. 100-250K	(3) MSA Pop. 250-500K	(4) MSA Pop. 500K-1M	(5) MSA Pop. 1-2.5M	(6) MSA Pop. 2.5-5M	(7) MSA Pop. 5M+
A. Unemployment Rate							
May 2020 - May 2019	6.417**	6.142**	7.845**	7.422**	8.568**	9.342**	10.382**
Apr. 2020 - Apr. 2019	8.597**	7.814**	9.471**	9.161**	10.306**	10.188**	11.123**
Mar. 2020 - Mar. 2019	-0.074	0.051	-0.607	0.296	0.638	0.396	1.259**
Feb. 2020 - Feb. 2019	0.537	-0.261	-0.560	-0.251	-0.508	-0.642	0.183
Jan. 2020 - Jan. 2019	0.034	-0.817	0.311	-0.668	-0.492	-0.422	-0.072
Diff.-in-Diff.	7.208**	7.497**	8.786**	8.751**	9.938**	10.295**	10.696**
DD St. Error	(0.490)	(0.696)	(0.661)	(0.492)	(0.442)	(0.470)	(0.402)
B. Labor Force Participation Rate							
May 2020 - May 2019	-0.032	0.355	-1.432	0.439	-1.258	-3.223**	-2.822**
Apr. 2020 - Apr. 2019	-1.388	-1.882	-0.262	-0.533	-1.866**	-3.336**	-3.563**
Mar. 2020 - Mar. 2019	0.035	-0.546	0.157	0.280	0.933	-0.614	0.014
Feb. 2020 - Feb. 2019	0.808	-0.209	-0.092	0.867	-0.279	-0.143	0.747
Jan. 2020 - Jan. 2019	0.751	-1.293	-0.762	0.378	0.392	0.699	0.846
Diff.-in-Diff.	-1.487	-0.008	-0.415	-0.672	-1.617*	-3.555**	-3.990**
DD St. Error	(0.773)	(1.121)	(0.989)	(0.765)	(0.668)	(0.725)	(0.584)
C. Employment-to-Population Ratio							
May 2020 - May 2019	-4.931**	-4.473**	-7.510**	-5.461**	-8.054**	-10.536**	-10.857**
Apr. 2020 - Apr. 2019	-7.784**	-7.836**	-7.684**	-7.705**	-9.985**	-11.307**	-12.085**
Mar. 2020 - Mar. 2019	0.089	-0.566	0.633	0.034	0.382	-0.918	-1.015
Feb. 2020 - Feb. 2019	0.363	0.003	0.358	1.038	0.146	0.388	0.574
Jan. 2020 - Jan. 2019	0.694	-0.604	-0.977	0.897	0.780	1.027	0.878
Diff.-in-Diff.	-6.881**	-5.844**	-7.283**	-7.556**	-9.485**	-11.625**	-12.198**
DD St. Error	(0.817)	(1.190)	(1.063)	(0.819)	(0.721)	(0.780)	(0.631)
D. Has Job Not at Work Rate							
May 2020 - May 2019	1.729**	2.014**	1.377**	1.904**	1.784**	1.434**	2.362**
Apr. 2020 - Apr. 2019	2.524**	3.671**	4.232**	3.276**	2.682**	2.055**	5.257**
Mar. 2020 - Mar. 2019	0.293	0.293	0.283	0.514	1.039**	0.772*	0.529*
Feb. 2020 - Feb. 2019	0.047	0.243	-0.134	-0.061	0.079	-0.210	-0.448*
Jan. 2020 - Jan. 2019	-0.437	0.021	-0.425	-0.270	0.026	-0.347	-0.359
Diff.-in-Diff.	2.321**	2.709**	3.077**	2.761**	2.183**	2.019**	4.217**
DD St. Error	(0.292)	(0.443)	(0.407)	(0.314)	(0.271)	(0.300)	(0.252)
E. Employed at Work Rate							
May 2020 - May 2019	-6.659**	-6.487**	-8.887**	-7.365**	-9.838**	-11.970**	-13.219**
Apr. 2020 - Apr. 2019	-10.308**	-11.506**	-11.917**	-10.981**	-12.667**	-13.362**	-17.342**
Mar. 2020 - Mar. 2019	-0.204	-0.860	0.351	-0.481	-0.657	-1.690*	-1.544*
Feb. 2020 - Feb. 2019	0.316	-0.240	0.492	1.099	0.067	0.598	1.022
Jan. 2020 - Jan. 2019	1.131	-0.625	-0.552	1.167	0.754	1.374	1.237*
Diff.-in-Diff.	-9.203**	-8.552**	-10.360**	-10.317**	-11.668**	-13.644**	-16.415**
DD St. Error	(0.837)	(1.225)	(1.096)	(0.845)	(0.745)	(0.808)	(0.652)

Notes: The sample includes civilians age 25-61. The table is otherwise equivalent to Table 1.
*Significantly different from zero at 5% level; ** Significant at 1% level.

Table A2: Employed at Work Rate Changes for the 50 Largest Population MSAs

	(1) 2019 Pop.	(2) April Diff.	(3) May Diff.	(4) Diff-in-Diff.	(5) DD St. Err.
New York-Newark-Jersey City, NY-NJ-PA	19.2M	-16.226**	-13.608**	-17.267**	(1.156)
Los Angeles-Long Beach-Anaheim, CA	13.2M	-15.516**	-14.767**	-15.631**	(1.347)
Chicago-Naperville-Elgin, IL-IN-WI	9.5M	-12.992**	-10.651**	-12.795**	(1.671)
Dallas-Fort Worth-Arlington, TX	7.6M	-15.121**	-6.092**	-8.760**	(1.909)
Houston-The Woodlands-Sugar Land, TX	7.1M	-9.150**	-4.547*	-8.054**	(2.055)
Washington-Arlington-Alexand., DC-VA-MD-WV	6.3M	-13.392**	-8.773**	-12.908**	(1.887)
Miami-Fort Lauderdale-Pompano Beach, FL	6.2M	-20.237**	-17.946**	-18.650**	(2.029)
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6.1M	-13.395**	-10.484**	-12.298**	(2.147)
Atlanta-Sandy Springs-Alpharetta, GA	6.0M	-11.457**	-10.979**	-12.833**	(2.101)
Phoenix-Mesa-Chandler, AZ	4.9M	-7.686**	-0.870	-5.662*	(2.257)
Boston-Cambridge-Newton, MA-NH	4.9M	-18.409**	-16.093**	-18.221**	(1.806)
San Francisco-Oakland-Berkeley, CA	4.7M	-13.057**	-13.658**	-15.535**	(2.255)
Riverside-San Bernardino-Ontario, CA	4.7M	-15.211**	-13.038**	-12.169**	(2.394)
Detroit-Warren-Dearborn, MI	4.3M	-21.084**	-18.824**	-19.739**	(2.381)
Seattle-Tacoma-Bellevue, WA	4.0M	-10.578**	-11.806**	-12.307**	(2.258)
Minneapolis-St. Paul-Bloomington, MN-WI	3.6M	-7.056**	-6.012*	-6.121*	(2.406)
San Diego-Chula Vista-Carlsbad, CA	3.3M	-13.433**	-10.871**	-10.778**	(2.726)
Tampa-St. Petersburg-Clearwater, FL	3.2M	-5.496	-7.033*	-6.778*	(2.806)
Denver-Aurora-Lakewood, CO	3.0M	-14.294**	-12.916**	-12.627**	(2.892)
St. Louis, MO-IL	2.8M	-11.420**	-9.894**	-13.107**	(2.910)
Baltimore-Columbia-Towson, MD	2.8M	-10.492**	-12.488**	-8.414**	(2.988)
Charlotte-Concord-Gastonia, NC-SC	2.6M	-13.984**	-8.355**	-7.703**	(2.960)
Orlando-Kissimmee-Sanford, FL	2.6M	-18.430**	-19.829**	-19.479**	(3.389)
San Antonio-New Braunfels, TX	2.6M	-14.608**	-10.547**	-10.177**	(3.333)
Portland-Vancouver-Hillsboro, OR-WA	2.5M	-8.170**	-6.155*	-8.921**	(2.488)
Sacramento-Roseville-Folsom, CA	2.4M	-8.912**	-10.563**	-6.735*	(3.217)
Pittsburgh, PA	2.3M	-17.303**	-11.177**	-11.189**	(3.159)
Las Vegas-Henderson-Paradise, NV	2.3M	-21.224**	-21.573**	-22.494**	(2.387)
Austin-Round Rock-Georgetown, TX	2.2M	-11.163**	-15.847**	-15.540**	(3.729)
Cincinnati, OH-KY-IN	2.2M	-13.934**	-13.103**	-11.699**	(3.606)
Kansas City, MO-KS	2.2M	-7.224*	-2.760	-5.744	(3.038)
Columbus, OH	2.1M	-9.969**	-9.256*	-10.003**	(3.672)
Indianapolis-Carmel-Anderson, IN	2.1M	-17.628**	-11.337**	-17.785**	(3.268)
Cleveland-Elyria, OH	2.0M	-16.725**	-11.995**	-13.883**	(3.603)
San Jose-Sunnyvale-Santa Clara, CA	2.0M	-15.195**	-15.272**	-17.345**	(3.535)
Nashville-Davidson--Murfreesboro--Franklin, TN	1.9M	-16.234**	-10.733**	-13.029**	(3.158)
Virginia Beach-Norfolk-Newport News, VA-NC	1.8M	-7.641	-0.736	-10.573*	(4.203)
Providence-Warwick, RI-MA	1.6M	-11.807**	-11.905**	-11.095**	(2.517)
Milwaukee-Waukesha, WI	1.6M	-15.104**	-8.239*	-7.552	(3.866)
Jacksonville, FL	1.6M	-3.984	-3.603	-6.600	(4.127)
Oklahoma City, OK	1.4M	-12.374**	-9.887**	-13.202**	(3.241)
Raleigh-Cary, NC	1.4M	-13.180**	-10.488*	-10.758**	(3.989)
Memphis, TN-MS-AR	1.3M	-9.167*	-10.112*	-1.921	(4.015)
Richmond, VA	1.3M	-5.458	-3.910	-3.678	(4.582)
New Orleans-Metairie, LA	1.3M	-21.005**	-13.462**	-14.929**	(3.277)
Louisville/Jefferson County, KY-IN	1.3M	-9.200*	-2.232	-7.252	(4.100)
Salt Lake City, UT	1.2M	-6.652*	-2.552	-3.399	(2.902)
Hartford-East Hartford-Middletown, CT	1.2M	-0.834	-6.642	-2.100	(4.024)
Buffalo-Cheektowaga, NY	1.1M	-16.059**	-11.446*	-14.803**	(4.891)
Birmingham-Hoover, AL	1.1M	-11.931**	-5.096	-5.266	(3.430)

Notes: The full sample includes civilians ages 16 and over. Columns (2) and (3) report year-over-year changes for April and May. The Diff.-in-Diff is computed via linear regression and measures an average effect for April-May 2020 relative to 2019 and January-February.
*Significantly different from zero at 5% level; ** Significant at 1% level.

Table A3: Separate Impacts of Including Subsets of Individual Controls

	(1)	(2)	(3)	(4)	(5)
MSA Pop. 100-250K × AprMay2020	-0.076	-0.827	-0.561	-1.390	-0.488
	(0.953)	(1.266)	(1.292)	(1.334)	(1.244)
MSA Pop. 250-500K × AprMay2020	-0.646	-1.596	-0.911	-2.107	-1.414
	(1.565)	(1.662)	(1.695)	(1.680)	(1.681)
MSA Pop. 500K-1M × AprMay2020	-1.149	-2.459*	-1.832	-3.327**	-2.134*
	(0.694)	(0.972)	(0.983)	(0.894)	(0.921)
MSA Pop. 1-2.5M × AprMay2020	-1.704*	-2.653**	-2.075*	-3.059**	-2.192*
	(0.770)	(0.872)	(0.908)	(0.832)	(0.846)
MSA Pop. 2.5-5M × AprMay2020	-3.541**	-3.780**	-2.952**	-4.652**	-3.598**
	(0.669)	(0.843)	(0.864)	(0.836)	(0.827)
MSA Pop. 5M+ × AprMay2020	-5.203**	-5.583**	-4.208**	-7.021**	-5.228**
	(0.721)	(0.866)	(0.916)	(0.830)	(0.850)
Age Dummies × Time Dummies	Yes	No	No	No	No
Gender Dummy × Time Dummies	No	Yes	No	No	No
Race & Ethnicity Dummies × Time Dummies	No	No	Yes	No	No
Education Dummies × Time Dummies	No	No	No	Yes	No
Married & Kids Dummies × Time Dummies	No	No	No	No	Yes
Local Area Variables × AprMay2020	No	No	No	No	No

Notes: The sample includes civilians age 16 and over. Standard errors in parentheses are clustered by local area. Regressions are similar to Table 3 Column 2 but separately control for subsets of individual controls.
*Significantly different from zero at 5% level; ** Significant at 1% level.

Table A4: Separate Effects for April and May 2020

	(1) April	(2) April	(3) May	(4) May
MSA Pop. 100-250K × AprMay2020	-0.587	2.459	-1.220	3.145*
	(1.613)	(1.786)	(1.438)	(1.585)
MSA Pop. 250-500K × AprMay2020	-0.739	3.178	-2.515	3.824
	(1.773)	(2.105)	(1.880)	(2.178)
MSA Pop. 500K-1M × AprMay2020	-2.432*	1.830	-2.641	4.178*
	(0.960)	(1.786)	(1.385)	(1.968)
MSA Pop. 1-2.5M × AprMay2020	-2.112	2.657	-3.177**	5.119*
	(1.139)	(2.210)	(1.064)	(2.047)
MSA Pop. 2.5-5M × AprMay2020	-2.697*	1.466	-4.789**	2.894
	(1.142)	(2.286)	(1.326)	(2.128)
MSA Pop. 5M+ × AprMay2020	-5.401**	0.317	-5.887**	4.212
	(1.044)	(2.786)	(1.135)	(2.573)
AprMay2020	-10.134**		-6.624**	
	(0.795)		(0.860)	
Ln COVID Case Rate by April 30 × AprMay2020		-1.756**		-2.011**
		(0.421)		(0.388)
% Voted Trump 2016 × AprMay2020		-0.037		0.047
		(0.043)		(0.034)
% Occ. Can Work from Home × AprMay2020		0.152		0.015
		(0.113)		(0.113)
% Employed in Construction × AprMay2020		0.270		0.226
		(0.205)		(0.222)
% Emp. Wholesale/Retail × AprMay2020		0.172		-0.224
		(0.184)		(0.221)
% Emp. Transportation/Utilities × AprMay2020		0.492*		0.523*
		(0.226)		(0.262)
% Emp. Professional Services × AprMay2020		-0.097		-0.039
		(0.145)		(0.149)
% Emp. Education/Health × AprMay2020		0.113		0.206
		(0.130)		(0.124)
% Emp. Leisure/Hospitality × AprMay2020		-0.556**		-0.596**
		(0.132)		(0.142)
% Emp. Other Services × AprMay2020		0.292		0.496
		(0.415)		(0.375)
% Emp. Public Administration × AprMay2020		0.269		0.044
		(0.142)		(0.159)
Ln Average Emp. Density × AprMay2020		-0.684		-0.725*
		(0.374)		(0.359)
Individual Characteristics × Time Dummies	No	Yes	No	Yes

Notes: The sample includes civilians age 16 and over. Standard errors in parentheses are clustered by local area. Regressions are similar to Table 3 except Columns (1) and (2) exclude May and Columns (3) and (4) exclude April. *Significantly different from zero at 5% level; ** Significant at 1% level.

Table A5: Results Using Alternative COVID-19 Infection Variables

	(1)	(2)	(3)	(4)
MSA Pop. 100-250K × AprMay2020	0.073	1.949	0.428	2.955
	(1.358)	(1.861)	(1.398)	(1.821)
MSA Pop. 250-500K × AprMay2020	1.323	3.365	1.292	4.110*
	(1.323)	(1.904)	(1.331)	(1.863)
MSA Pop. 500K-1M × AprMay2020	0.888	3.039	0.875	3.844*
	(1.286)	(1.978)	(1.351)	(1.946)
MSA Pop. 1-2.5M × AprMay2020	1.461	3.996	1.327	4.843*
	(1.429)	(2.329)	(1.495)	(2.275)
MSA Pop. 2.5-5M × AprMay2020	0.076	2.499	0.118	3.460
	(1.789)	(2.505)	(1.982)	(2.600)
MSA Pop. 5M+ × AprMay2020	-0.951	2.148	-1.147	3.166
	(1.761)	(2.912)	(1.844)	(2.896)
% Voted Trump 2016 × AprMay2020	0.010	0.012	0.011	0.015
	(0.033)	(0.032)	(0.035)	(0.033)
% Occ. Can Work from Home × AprMay2020	0.072	0.072	0.077	0.075
	(0.117)	(0.119)	(0.121)	(0.123)
% Employed in Construction × AprMay2020	0.196	0.183	0.174	0.159
	(0.185)	(0.183)	(0.188)	(0.185)
% Emp. Wholesale/Retail × AprMay2020	0.021	-0.025	0.062	-0.010
	(0.196)	(0.194)	(0.205)	(0.202)
% Emp. Transportation/Utilities × AprMay2020	0.418	0.437*	0.389	0.420
	(0.213)	(0.219)	(0.221)	(0.228)
% Emp. Professional Services × AprMay2020	-0.139	-0.076	-0.168	-0.077
	(0.159)	(0.170)	(0.166)	(0.177)
% Emp. Education/Health × AprMay2020	0.123	0.160	0.080	0.140
	(0.097)	(0.107)	(0.100)	(0.110)
% Emp. Leisure/Hospitality × AprMay2020	-0.532**	-0.560**	-0.562**	-0.596**
	(0.117)	(0.115)	(0.120)	(0.116)
% Emp. Other Services × AprMay2020	0.420	0.369	0.524	0.437
	(0.408)	(0.414)	(0.418)	(0.426)
% Emp. Public Administration × AprMay2020	0.158	0.133	0.183	0.145
	(0.111)	(0.110)	(0.116)	(0.114)
Ln Average Emp. Density × AprMay2020		-0.604		-0.832*
		(0.430)		(0.414)
Ln COVID Death Rate by April 30 × AprMay2020	-1.724**	-1.535**		
	(0.261)	(0.308)		
Ln COVID Death Rate by May 31 × AprMay2020			-1.533**	-1.311**
			(0.267)	(0.285)
Individual Characteristics × Time Dummies	Yes	Yes	Yes	Yes

Notes: The sample includes civilians age 16 and over. Standard errors in parentheses are clustered by local area. Regressions are similar to Table 3 except use different COVID-19 variables.
*Significantly different from zero at 5% level; ** Significant at 1% level.

Table A6: DDD Regression Results with State × Time Effects

	(1)	(2)	(3)	(4)
MSA Pop. 100-250K × AprMay2020	-1.068	-0.428	1.072	3.002
	(1.088)	(0.933)	(1.147)	(1.755)
MSA Pop. 250-500K × AprMay2020	-0.693	0.254	2.520*	4.645*
	(1.179)	(0.991)	(1.241)	(1.981)
MSA Pop. 500K-1M × AprMay2020	-2.440**	-1.241	1.274	3.545
	(0.876)	(0.951)	(1.214)	(2.011)
MSA Pop. 1-2.5M × AprMay2020	-1.712	-1.168	2.937	5.464*
	(1.004)	(0.895)	(1.560)	(2.409)
MSA Pop. 2.5-5M × AprMay2020	-2.252*	-3.183**	1.241	4.035
	(1.092)	(0.941)	(1.915)	(2.909)
MSA Pop. 5M+ × AprMay2020	-4.862**	-4.820**	0.828	3.878
	(1.066)	(0.962)	(2.004)	(3.088)
Ln COVID Case Rate by April 30 × AprMay2020			-1.701**	-1.532**
			(0.535)	(0.524)
% Voted Trump 2016 × AprMay2020			0.016	0.009
			(0.046)	(0.046)
% Occ. Can Work from Home × AprMay2020			-0.026	-0.029
			(0.114)	(0.113)
% Employed in Construction × AprMay2020			-0.030	-0.039
			(0.219)	(0.216)
% Emp. Wholesale/Retail × AprMay2020			-0.104	-0.134
			(0.190)	(0.189)
% Emp. Transportation/Utilities × AprMay2020			0.371	0.377
			(0.254)	(0.254)
% Emp. Professional Services × AprMay2020			-0.166	-0.103
			(0.143)	(0.142)
% Emp. Education/Health × AprMay2020			0.174	0.181
			(0.125)	(0.125)
% Emp. Leisure/Hospitality × AprMay2020			-0.495**	-0.515**
			(0.166)	(0.167)
% Emp. Other Services × AprMay2020			0.460	0.423
			(0.308)	(0.312)
% Emp. Public Administration × AprMay2020			0.130	0.087
			(0.156)	(0.155)
Ln Average Emp. Density × AprMay2020				-0.627
				(0.451)
Individual Characteristics × Time Dummies	No	Yes	Yes	Yes

Notes: The sample includes civilians age 16 and over. Standard errors in parentheses are clustered by local area. Regressions are similar to Table 3 but include state × time effects.
*Significantly different from zero at 5% level; ** Significant at 1% level.