Lessons from the 2020 Covid Recession for Understanding Regional Resilience

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Abstract: The recession caused by the 2020 Covid-19 pandemic differs from previous recessions due to the immediate economic collapse following President Trump's national emergency declaration on March 13, 2020 and due to changes in the sectors of the economy that were adversely impacted stemming from fears of contracting and spreading the disease. Using county-level data, we identify the effect of the Covid-19 pandemic and accompanying state and local stay-at-home orders on economic outcomes, including consumer spending, unemployment insurance claims, time spent at home and time spent at work, small business openings and revenue, and low-income employment and earnings. We then discuss heterogeneity in these effects related to pre-pandemic county characteristics, including industrial composition, small-firm employment, and educational attainment, and show that the impacts differ from previous recessions. For example, we find that counties with larger shares of employment in leisure services, as opposed to manufacturing, were more adversely affected, but counties with higher shares of less-educated and young workers fared better, likely due to less-educated and young workers being disproportionately employed in "essential" jobs. In addition, we find ambiguous effects of a county's firm-size structure, in contrast with the regional resilience literature documenting its effectiveness in mitigating the effects previous economic downturns.

1. Introduction—Setting the Economic Stage

The 2020 Covid-19 pandemic created a global health crisis not seen since the Spanish Flu a century ago. As of mid-December 2020, the website Worldometer recorded nearly 1.7 million global deaths from Covid-19, including 318,000 in the United States, the hardest hit country.[1] U.S. daily mortality from Covid routinely exceeds 3,000, which is greater than the number of people who perished during the 9/11 terrorist attacks.

Covid-19 was first detected in Wuhan, China in late 2019. The first confirmed U.S. cases occurred in January 2020, though later it was discovered that Covid was circulating undiscovered in the U.S. in December 2019 (Basavaraju, 2020).[2] U.S. cases began to explode in March, leading to the cancellation of high-profile sporting events. President Trump's March 13th national emergency declaration led to a cascading set of nonessential-business shutdowns across most U.S. states by the end of March, though some prominent holdouts included the Dakotas, Nebraska, and Iowa. Even where shutdowns were not enforced, fears of Covid initially led to plunges in economic activity.

Early Covid hotspots in the United States included parts of the west coast, New York, New Jersey, and Connecticut, before spreading to parts of Louisiana, Illinois, Massachusetts, and Michigan. After the initial severe spike, cases plateaued in mid-April through late June, before rising again in July, followed by an even more deadly upturn starting in mid-October.

The Covid-19 shutdown dramatically affected the national and regional economies in unusual ways. Standard recessions tend to concentrate in certain sectors and regions due to factors such as popping of asset-valuation "bubbles," financial crises, or demand or supply

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[1] Total U.S. Covid deaths exceed American combat deaths in World War II. Brazil had the second most deaths at 185,000. [https://www.worldometers.info/coronavirus/]

[2] CDC, https://www.cdc.gov/media/releases/2020/s0126-coronavirus-new-cases.html.

shocks—e.g., monetary policy mistakes or oil price shocks. Much like a natural disaster such as an earthquake, hurricane, or flood, the Covid outbreak immediately led to much of the economy shutting down. Yet, the Covid recession differs from those caused by natural disasters because its effects were not localized as, say, from a hurricane. Certainly, there are supply-chain effects from a natural disaster when important inputs are concentrated near the disaster, but the Covid recession led to massive supply-chain disruptions on a global and national scale, complicated by efforts to mitigate the spread of disease. Given that climate change may increase the likelihood of pandemics, as well as the frequency and scale of other natural disasters, understanding the Covid recession is critical for understanding resilience, especially given some of the novel policy measures that have been implemented to address the economic crisis.

As discussed in more detail below, the Covid recession diffused across U.S. regions differently than "normal" recessions, as the intervening effects of local industry composition, demographic composition, firm-size structure, etc. worked differently. In addition, the stimuluses provided by the federal government and Federal Reserve occurred more rapidly and on a grander scale than ever before. Federal stimulus efforts also included novel programs that, in turn, influenced the spatial effects. Therefore, a main contribution of this study is to empirically assess the local severity of the Covid recession and identify *why* and *how* this recession differed from typical downturns.

Laying the national stage. Figure 1 shows total U.S. employment benchmarked to February 2020=100. The figure first reports nonfarm payroll employment—which is viewed as relatively more accurate because it is based on a firm survey but does not include self-employed, farm workers and counts multiple jobholders numerous times. The figure also reports the Current Population Survey (CPS)'s employment estimate because it includes the omitted workers missed in the firm survey without counting each job held by multiple jobholders. The values are not seasonally adjusted because the seasonality means little relative to the effects of Covid.

Figure 1 shows that between February and April 2020, as the economy shutdown, U.S. employment declined by 16% using the more inclusive household survey or by 14% using the Bureau of Labor Statistics (BLS) firm survey—i.e., a remarkable 24.7 million fewer employed using the CPS survey. This economic pain does not include the corresponding 4.3 million to 10.9 million worker increase in those employed part-time due to economic conditions.[3] Such a rapid U.S. economic calamity has never occurred before. In the first two months of the Great Recession, nonfarm employment declined only 0.1%, and even at the employment trough (in both the firm and household surveys), the decline was only 6.3%.[4] In the Great Depression, for the first *two years* after September 1929's peak, nonfarm employment declined 19.2%.[5]

Almost as remarkable as the sharp decline was the ensuing rebound as the economy reopened in May 2020. Between April and July, nonfarm payrolls rose 7.6%. Yet, job growth slowed considerably to 2.2% between July and November 2020, remaining 6.5% below the February peak (or, a greater decline than at low-point of the Great Recession), while the November household employment survey even indicated an employment decline. Thus, the slowing of U.S. job growth represents is another atypical trend, exacerbated as the second surge of Covid took off in early summer.

Covid Recession and Different Spatial Impacts. The national trends obscure significant

[3]For perspective, the BLS estimated that the total civilian labor force was 160.5 million in February. The part-time employment data is from Table A7 of the BLS monthly employment situation release. Only seasonally-adjusted data is available in that source.

[4] The corresponding peak-to-trough employment decline in the household survey was 5.6%.

[5]The decline in nonfarm employment from the Great Depression's September 1929 peak to its trough in March 1933 was 33.9%--i.e., while the Covid recession was vastly more sudden, it was less severe than the peak of the Great Depression. Downloaded from the Federal Reserve Bank of St. Louis (FRED): Employees in Nonagricultural Establishments, U.S. Vintage: 2005-08-01, Millions of Persons, Monthly, Not Seasonally Adjusted, NBER, Series #M0868AUSM148NNBR_20050801. [https://alfred.stlouisfed.org], December 18, 2020.

regional variation in the downturn and subsequent recovery. Figures 1a and 1b illustrate large differences in nonfarm state employment growth rates for the collapse and initial recovery, respectively. In the early period, job losses varied from -7.6% in Oklahoma to -23.1% in Michigan. Subsequent job growth then ranged from 2.1% in District of Columbia to Michigan's 20.1% in the latter period.

Wide divergence across regions is further reflected by the changing standard deviation in job growth. For example, for the pre-Covid February 2019-February 2020 period, the standard deviation of nonfarm job growth across the "51" states equaled 0.93% but was nearly 3% for the February-October 2020 period. Splitting the post-Covid era into growth and recovery periods, the standard deviation was 3.87% between February and April and 3.50% in the seven-month April to October period—i.e., both periods were much more variable than the pre-Covid period. Even over the 26-month Great Recession employment peak-to-trough period running from December 2007 to February 2010, the standard deviation across states equaled 2.86%, with job growth only ranging from Nevada's -15.0% to Alaska's 0.8%.

Economic activity collapsed in the Covid-ravaged Northeast through April-May, as it did in tourist locations such as Nevada and Hawaii, even though they were not particularly hit hard by the disease. While tourist destinations typically struggle during recessions, the full extent of their downturn is usually delayed until the recession matures. More consistent with the standard pattern, Florida and Louisiana, also tourist destinations, initially avoided much of the initial plunge. Florida had fewer Covid-based restrictions during peak Spring-break season, while Louisiana's patters are more difficult to explain due to the severe nature of its Covid outbreak (Mardi Gras was a super-spreader event).

The performance of the Great Lakes states during the Covid recession is unusual because it usually leads the country into recession due to its manufacturing intensity, as households cut back large durable goods purchases and business limits investment (e.g., see the overview in Partridge and Rickman, 2003). In this case, even as Michigan led the country into recession in terms of job losses, the other Great Lakes states performed closer to the U.S. average, including Illinois which was initially hit hard by Covid.

Spatial variation in the recovery in May is also not easily explained by "typical" patters. There are clear cases of reversion to the mean such as the rapid recovery of hard-hit Michigan and Nevada, or the relatively small bounce-back in the less-hit Plains states running from Oklahoma up through the Dakotas. However, hard-hit states such as Hawaii, some of the Northeast states, and California do not simply revert to the mean as evidence by their lagging recoveries. Likewise, Kentucky's strong performance since April is somewhat of an outlier.

The next section of the paper discusses some of the relevant economic-recession literature to motivate the hypotheses that we consider in the empirical analysis. The following sections discuss the data and empirical implementation. In particular, we discuss some of the high-frequency U.S. county-level data employed to assess highly-localized effects. The next section presents our empirical results, focusing on aggregate county-level economic conditions and related impacts on vulnerable low-income workers and on the critical effects on small-business start-ups that shape future economic expansions at the local and national levels. We then follow with some concluding discussion of the implications of our study and future paths for possible research.

2. Literature Review

There is growing research on how the COVID-19 pandemic has affected the global economy and local economies throughout the world. Our literature review focuses on studies that examine the effects of Covid-19 on the overall U.S. economy and on U.S. subregions/cities because of its relevance for drawing comparisons and to illustrate our contributions. Within this subset, we emphasize research that examines the pandemic's effects on the broader labor market, particularly focusing on identifying heterogeneous effects of the pandemic by industry and occupation, worker characteristics, local demographics, and distribution of local firm sizes.

2.1 Heterogenous Effects by Industry and Occupation

The first group of studies we discuss seeks to identify the industries and occupations most impacted by the COVID-19 pandemic in the United States. The scope of which, of course, changed as health conditions changed, the overall government response shifted, and the economy adjusted to the initial shocks, including a major shutdown. Using big data on job-vacancy postings in the United States, Campello, Kankanhalli, and Muthukrishnan (2020) find larger hiring declines for jobs defined as high-skill (e.g., CEOs, lawyers, post-secondary teachers, statisticians, and physicians) relative to low-skill jobs (farming, food services, landscaping, garment, and timber logging workers). As the authors note, this finding is somewhat unexpected because less-skilled workers typically suffer the most during a recession (Hershbein and Kahn, 2018). The authors explain this finding by citing reports of expedited hiring into low-skill occupations early in the pandemic (Gelles and Corkery, 2020). The raw data tell a little more nuanced story. While the overall unemployment rate rose from 3.5% in February 2020 to 14.7% in April 2020, the corresponding change for those with less than a high school degree rose from 5.7% to 21.2% (a 272% increase) versus 1.9% to 8.4% (a 342% increase) for those with at least a Bachelor's degree (for the population over 25 years old).[6] That is, the percentage-point change

[6] The pattern follows across other education groups. For high school graduates and no college, the corresponding February to April 2020 U.S. unemployment rates changed from 3.6% to 17.3% (a 381% increase) and from 3% to 15% (a 400% increase) for those with some college or an Associate's degree. However, the unemployment rate understates the challenges faced by the less educated as a large share exit the labor-force. For example, between February and April 2020, the labor-force participation rates of less skilled workers fell from 47.8% to 42.8% while

was much more for the less educated but the increase was less in relative terms.

Using (different) jobs-posting data, Forsythe et al. (2020) find that almost all industries and occupations experienced hiring reductions and spikes in unemployment insurance (UI) claims in March and April 2020, with leisure and hospitality services and "nonessential" retail sectors faring the worst and "essential" retail faring the best. They conclude that, because of the pervasive nature of the decline across sectors, local stay-at-home orders were not the main driver of the economic collapse. Similarly, Rojas et al. (2020) identify the effect of specific mitigation policies enacted by local governments on economic activity and find, consistent with Forsythe et al. (2020), that large increases in UI claims in late March occurred for almost all sectors and in all states, reaching a similar conclusion: because all sectors saw large spikes in UI claims, the economic disruption was caused primarily by the virus-induced health shock and not by specific, local mitigation policies aimed at stopping the spread.

Many studies, unsurprisingly, find more pervasive adverse employment effects in industries and occupations that are less apt to be performed remotely. Using monthly data from the Current Population Survey (CPS), Montenovo et al. (2020) find larger job losses among occupations requiring interpersonal contact and those where remote work is impossible. Similarly, using the American Time Use Survey, Papanikolaou and Schmidt (2020) find that sectors with larger shares of workers that are unable to work remotely experienced larger employment declines during the pandemic. They also show that establishments deemed essential experienced smaller declines in foot traffic relative to non-critical industries, suggesting that essential businesses had less severe job losses than those for non-essential businesses.

2.2 Heterogenous Effects by Worker Characteristics

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the corresponding rates for those with a Bachelors Degree or higher was 73.1% to 71.6% (for those over 25 years old). The data source is the Bureau of Labor Statistics (BLS).

The second subset of COVID-19 studies related to ours examines heterogenous effects of the pandemic on labor market outcomes for different types of workers, conditional on their pre-pandemic industry and occupation.

Montenovo et al. (2020) use monthly CPS data to examine how the Covid-19 economic shutdown differentially affected specific types of workers and occupations. They find larger employment declines in April and May 2020 among Hispanic workers, young workers, and workers with high school degrees and some college. More importantly, they find that even after controlling for how certain demographic groups sorted (pre-Covid) into some occupations, job-loss differences persist across groups.

Similarly, Fairlie et al. (2020) find that Latinx workers were disproportionately hurt by Covid-19 unemployment relative to white workers and that this effect is partly attributable to lower skills and to higher employment concentrations in occupations that were hardest hit by the pandemic. In contrast, Black workers were not disproportionately affected relative to white workers in April 2020, and being more concentrated in occupations less affected by the Covid shutdowns relative to Latinx workers helped partially protect them.

Papanikolaou and Schmidt (2020) find higher probabilities of nonemployment among women and lower-earnings workers, with the largest adverse effects for females without a college degree and with young children. Bui, Button, and Picciotti (2020) examine the differential effect of the pandemic on workers by age group, finding that workers over 65 were disproportionately affected, with the unemployment rate for that group rising to 15.4 percent, compared to 13 percent among workers aged 22 to 44. Consistent with Papanikolaou and Schmidt (2020), they find evidence that women of all age groups were disproportionately adversely affected. One reason for these gender disparities is that jobs deemed essential such as warehousing or delivery are disproportionately male. However, another explanation is that mothers were more likely to be charged with helping their children with online schooling, hence the nickname for the Covid recession: the "She-cession."[7]

Lastly, Borjas and Cassidy (2020) use monthly CPS data to assess how the pandemic affected immigrant workers relative to natives. They find that immigrants –undocumented males, in particular – were especially hurt by the pandemic, experiencing more severe employment losses than native men, which they attribute to immigrants being less likely to be employed in jobs allowing remote work.

In contrast to the other studies, Cheng et al. (2020) examine not how the COVID-19 pandemic and subsequent economic shutdown affected specific groups of workers, but instead how the *reopening* of businesses in early summer 2020 differentially impacted different groups of workers. Using CPS data, they unsurprisingly find that reemployment rates were relatively high and that many workers were reemployed by previous employers, suggesting that most of the employment increase resulted from people returning to previously existing jobs. Comparing demographic groups, they find that the probability of reemployment in May 2020 is higher for groups who had the lowest unemployment in April 2020. Specifically, they find that men, non-Hispanic whites, and prime-aged individuals were all less likely to be unemployed during the pandemic and therefore, conditional on being unemployed, were more likely to be reemployed when businesses reopened.

2.3 Effects on Small Businesses

The final subset of relevant studies discuss how the Covid-19 pandemic affected small businesses. Many of the studies directly surveyed small businesses for a better understanding of

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[7]For example, see "The FRED Blog: The Covid-induced "She-cession." [available at: https://fredblog.stlouisfed.org/2020/11/the-covid-19-induced-she-cession/. Downloaded December 17, 2020.]

the unique effects of the pandemic. For example, Bartik et al. (2020) surveyed more than 5,800 U.S. small businesses in late March 2020. They find that most are financially fragile and plan to seek funds through the Coronavirus Aid, Relief, and Economic Security (CARES) Act. They cite firm concerns about accessing aid because of bureaucratic issues and difficulty establishing eligibility. Similarly, Humphries, Neilson, and Ulyssea (2020) surveyed 8,000 small business owners in late March and early April 2020, finding similar bleak expectations and that the smallest businesses had the least knowledge of government assistance programs after the CARES Act passed. They conclude that small businesses may have missed out on funds from the Paycheck Protection Program (PPP) because of differential information relative to larger firms.

Alekseev (2020) uses a Facebook survey in late April 2020 among frequent sellers on Marketplace, Facebook's e-commerce platform. They found that older and larger businesses were more likely to be open during the survey, as were businesses employing more men. They report that most businesses experienced reduced workloads and that many changed business operations—e.g., increasing their online presence, expanding digital payments, using delivery services and/or curbside pickup. The authors also found that many small businesses struggled financially and expressed concerns about future cash flow. 44.5 percent of small business respondents reduced the number of active employees, which is consistent with Campello, Kankanhalli, and Muthukrishnan (2020) who find a much larger decline in job postings among small firms than for larger firms due to the pandemic. Further, they find that firms with fewer in-person interactions were least likely to lay off workers.

Using nationally representative data from the April 2020 CPS, Fairlie (2020) finds that the number of active small business owners declined by 22 percent between February and April 2020 with losses across almost all industries. The number of active small business owners remained low in May and June, and he finds differential pandemic effects on small businesses related to the owner's demographic characteristics, with worse outcomes for African-American, Latinx, and Asian businesses relative to businesses owned by whites. Similarly, he finds evidence that immigrant- and female-owned businesses were disproportionately affected. Finally, Kim, Parker, and Schoar (2020) provide evidence that both small business revenue *and* the spending of their owners declined by about 40% following President Trump's national emergency declaration in March 2020. The authors show that most of the small business revenue declines are attributable to national factors as opposed to local policies or infections.

In contrast with other studies that generally aggregate small businesses into one category, Bartlett and Morse (2020) use data from Oakland, California to appraise whether the ability of small businesses to survive the pandemic depends firm size. They find that a low-cost structure helps non-employer businesses survive amidst substantial declines in store foot traffic and that revenue resiliency aids businesses with 1-5 employees. Lastly, they find that although businesses with 6 to 50 employees have more labor flexibility, they have greater closure risk because of sunk costs. Lastly, they provide evidence of the PPP's effectiveness in improving medium-run survival probabilities, but only among very small businesses.

3. Data

3.1 Dependent Variables

Our sample includes the approximately 3,100 U.S. counties (or equivalents). Some samples are split into metropolitan and nonmetropolitan definitions using official definitions. Our dependent variables are defined as follows using UI claims to demonstrate:

$$\Delta UI_{ct} = \frac{UI_{ct} - AvgUI_{cb}}{AvgUI_{cb}}$$

where UI_{ct} is the number of UI claims filed in county c in week t and where $AvgUI_{cb}$ is the average number of weekly UI claims in county c during the baseline period, defined as January 2020 and February 2020. This variable is defined for the week of January 11, 2020 through the week of July 4, 2020.

The remaining dependent variables are derived from a publicly-available

data

base built by Raj Chetty, John N. Friedman, Nathaniel Hendren, Michael Stepner and

the

Opportunity Insights Economic Tracker Team using anonymized private data.

Aggregate consumer spending data are based on credit- and debit-card spending data from Affinity Solutions. The raw data contain the daily change in average credit and debit card spending by county, indexed to January 4-31, 2020 and seasonally adjusted.

Low-income earnings and employment come from Earnin and Homebase and are defined daily from January 8, 2020 through May 30, 2020, relative to the January 8-31, 2020 average. Low-income is defined as the median annual income for those earning less than $20,000.

Small business openings and revenue data are from Womply and are defined daily from January 10, 2020 through July 8, 2020. These data are a seasonally-adjusted seven-day moving average of the percent change in the number of small businesses that open and the percent change in small business revenue, compared to the January 4-31, 2020 average.

Lastly, mobility data come from the Google COVID-19 Community Reports and are defined daily from February 24, 2020 through July 10, 2020. Time spent away from home and time spent at the workplace are obtained from GPS data and are reported relative to the January 3, 2020 through February 6, 2020 average.

The dependent variables typically span the January 1 to June 30, 2020 period. This period has the advantage of capturing the initial Spring 2020 surge in Covid cases and the subsequent downturn from late April through late June when cases approximately reached their nadir. The sample period also captures changes in the unemployment insurance (UI) system that greatly expanded eligibility and the financial benefits (described more below), for which the expanded benefits were about to expire (the UI expanded benefits expired July 31, 2020.) Likewise, the main surge in small-business relief had nearly run its course by the end of the sample period, while other key stimulus programs had also mainly concluded. Thus, the sample period reflects key institutional program differences from past recessions and the concluding the sample period June 30 allows us to avoid the vexing empirical problem of accounting for the second surge in Covid infections beginning in July 2020 and the slowing of economic growth.

3.2 Explanatory Variables

We included the following set of explanatory variables in our model after examining the relevant regional growth and labor literatures and after reading the emerging literature on the types of work and firms disproportionately affected by the pandemic and subsequent shutdowns.

First, we include four variables that reflect the county's industry composition, which leads to differential impacts on regional economic growth and local labor markets. As discussed in related regional studies, industry employment shares are important controls regarding the ability of counties to adapt and grow during a recession (Partridge and Tsvetkova, 2020; Tsvetkova, Partridge and Betz, 2019). For example, manufacturing historically plays an outsized role in shaping which regions are most affected by recessions. Second, we include variables describing the distribution of employment by firm size because small firms have been disproportionately (negatively) affected by the shutdowns.

Next, we include a variable grouping describing a county's population and workforce. For example, we include population size due to the importance of agglomeration for growth (Martin and Ottaviano, 2001), and we include measures of educational attainment due to the role of human capital in attracting fast-growing, skill-intensive industries (Glaeser and Saiz, 2003) and its positive impact on future regional human capital levels (Chung and Partridge, 2019; Chung, Zhang and Partridge, 2020). Also, at least initially, Covid spread faster in larger cities. Finally, we include measures of the racial, ethnic, and immigrant composition of the population because variation in these factors have been linked to regional productivity (Bellini, Ottaviano, Pinelli, and Prarolo, 2013; Lewis and Peri, 2015) and responses to recessions.

We use the 2018 American Community Survey (ACS) 5-year estimates to obtain pre-pandemic, county-level socioeconomic characteristics. Specifically, we include population shares for two education categories (high school dropouts, high school graduates and those with some college experience, with the share having a bachelor's degree or higher being the omitted group), population shares for five racial and ethnic categories (Black, Asian, white, other race, and Hispanic), population share of foreign-born immigrants, and the share of total employment that is self-employed.

We use employment data from County Business Patterns (CBP) from the U.S. Census Bureau to identify industry employment shares for each county pre-pandemic. Because CBP county/industry data is often suppressed for confidentiality reasons, we use data from the W.E. Upjohn Institute for Employment Research that estimates the suppressed values in the original CBP data (Bartik, Biddle, Hershbein & Sotherland, 2018) using an algorithm from Isserman and Westervelt (2006). From this, we derive the 2016 total employment shares in the following industries: arts, entertainment, recreation, accommodation and food services (which we refer to as leisure services); manufacturing; agriculture, mining, fishery, and forestry (which we refer to as agriculture and mining moving forward); and public service.

We use the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Quarterly Workforce Indicators (QWI) in our derivation of the pre-pandemic firm-size distribution. We obtain total employment for each county and firm employment for the following five firm-size employment categories: 0-19, 20-49, 50-249, 250-499, and greater than or equal to 500 employees. The data are from the fourth quarter of 2017 for all states except South Dakota because it is the latest available data. Fourth quarter of 2016 is used for South Dakota because 2017 data is unavailable.

We standardize all dependent and independent variables by subtracting off the mean and dividing by the standard deviation to be able to easily compare the relative magnitudes of our coefficient estimates. This enables us to interpret our regression coefficients as the standard deviation change in the dependent variable attributable to a one standard deviation change in the explanatory variable (often referred to as beta coefficients).

4. Empirical Specification

The unanticipated nature of the Covid-19 pandemic allows us to identify the effect of the pandemic and accompanying state and local stay-at-home orders on economic outcomes for U.S. counties. Following the President's March 13, 2020 national emergency declaration, economic activity across the country plummeted as "nonessential" businesses closed. Yet, the magnitude of the economic collapse varied across the nation, in part due to differences in pre-pandemic county characteristics such as industry composition. To identify the extent to which pre-pandemic characteristics contributed to the economic decline experienced in subsequent weeks and months, we regress county-level measures of economic activity on our main regressors of interest, an interaction term between a dummy variable equal to 1 for days (or weeks) after March 13, 2020 and a vector of pre-pandemic county characteristics. The size of the estimated coefficients on these interaction terms measure how the economic impact of the pandemic changes with respect to marginally higher values of each county characteristic, conditional on all others.

We estimate the following econometric equation:

$$Y_{ist} = \alpha + \theta * COVID_t + \sum \beta_j * COVID_t * A_{isj} + \sum \gamma_j * A_{isj} + \delta_s + \mu_t + \varepsilon_{ist} \quad (1)$$

where Y_{ist} is the economic outcome of interest for county i in state s at time t. $COVID_t$ is a dummy variable equal to 1 for all days (or weeks) after March 13, 2020 and 0 otherwise. A_{isj} is a pre-pandemic characteristic j of county i in state s that may influence how COVID-19 affected subsequent economic outcomes. δ_s are state fixed effects that control for time-invariant state characteristics correlated with pre-pandemic county characteristics and subsequent changes in county-level economic outcomes, like differences in state regulatory and tax regimes or unemployment systems, or state-level Covid mandates. For example, UI insurance regimes are set by each state such as benefit levels and eligibility requirements (except for *ad hoc* Pandemic Unemployment Assistance (PUA) rules such as for "gig" workers and the federal $600 PUA top-up). Other state effects include differing state UI computer systems, in which states with the most antiquated software had a collapse of their system, leading to multiple UI filings by the same individual or weeks delay in receipt of benefits.[8]

We include day or week fixed effects, μ_t (in the case of weekly UI claims growth rate, μ_t is week fixed effect), to control for national pandemic-related shocks common to all counties. For example, if there is a common national effect such as national fear of the virus, the national

[8] The GAO (2020) found that reported weekly UI Claims have been overestimated during the Covid-pandemic period. The GAO points to the main cause being problems related to antiquated UI software at the individual state level. Thus, state fixed effects should generally account for this concern (as well as the time-period fixed effects).

shutdown in latter March and most of April, or significant economic improvements beginning at the end of April, these fixed effects will capture those factors. Finally, for all $j = 1 \dots J$, β_j is our coefficient of the interest, which measures the differential effect of the COVID-19 pandemic for counties with differing pre-pandemic levels of characteristic A_j—i.e., when the explanatory variable is interacted with the Covid indicator (for weeks after the week of March 13). The residuals are assumed to be clustered at the county level.

Further concerns about possible county-level time-invariant fixed effects are mitigated by the construction of the dependent variables. Specifically, when constructing our dependent variables, we divide changes in each economic outcome by the January 2020 baseline level of that economic outcome before the pandemic took hold. By constructing our dependent variables in this manner, any remaining time-invariant county effects (not captured by state fixed effects) are in both the numerator and denominator of the dependent variable and, consequently, cancelled out. Another advantage of our empirical specification is we control for the key pre-pandemic underlying socioeconomic conditions in addition to the fixed effects, reducing the probability that omitted variables are tangibly affecting the results. The descriptive statistics for our key variables are reported in Table 1.

5. Empirical Results

We now turn to the regression results. In our discussion, we focus on the Covid-period interactions with the explanatory variables to assess whether differing initial characteristics explain the economic outcomes. The main explanatory variable effects are not reported, but they are almost all statistically insignificant, suggesting that at least initially, the fixed effects generally account for differential outcomes across counties. The main Covid period effect (i.e., θ in Equation 1) is reported at the bottom of the respective tables, indicating the unsurprising result that economic activity was greatly depressed after March 13, all else equal. To aid in interpreting the results, we report standardized regression coefficients that represent the standard deviation change in the dependent variable in response to a one-standard deviation change in the explanatory variable. Likewise, for results that are statistically significant at the 1%, 5%, or 10% levels, the coefficients are shaded green if the result suggests stronger local activity and "burnt" orange if it implies weaker activity.

5.1 Aggregate Consumer Spending

We begin by examining how the Covid-19 pandemic affected consumer spending with the results being reported in Table 2. We center our discussion on the pooled regression results in column (1) for the most part, though we also discuss the "urban" metro results and "rural" nonmetro results in columns (2)-(3). The results suggest that counties with higher shares of employment in leisure services and manufacturing experienced greater reductions in consumer spending immediately following the national emergency declaration. It is unsurprising that having a greater share of employment in leisure services is negatively related to overall sales as restaurants, bars, and hotels, especially in tourist destinations such as Hawaii, were devastated by initial effects of Covid-19. A one-standard deviation increase in leisure services is associated with a 0.06 standard deviation decrease in consumer spending, all else equal. Specifically, a one-standard deviation increase in the manufacturing employment share is associated with a 0.08 standard deviation decrease in consumer spending. While the larger role of leisure services in leading the county into recession is unusual, the localized role manufacturing plays is somewhat similar to past patterns (Partridge and Rickman, 2002).

The results in columns (2) and (3) indicate that that both the leisure services and manufacturing share results are driven largely by spending declines in nonmetro counties whose employment is relatively more concentrated in those two industries, while the corresponding responses in metro counties is statistically insignificant. In contrast, we do not find a statistically significant effect of the pandemic on consumer spending in counties with larger shares of agriculture and mining or public sector employment. Chetty et al. (2020) conclude that the drop in U.S. consumer spending in response to the Covid-19 pandemic was proportional to the degree of possible physical exposure to the virus across sectors. Our results partially support their conclusion since the potential for exposure in leisure services and in certain manufacturing subsectors, where workers often work inside in close physical proximity to one another, are high relative to exposure in agricultural or public sector work. Yet, it is less clear if this is the case for the omitted category, other services.

The effects of the pandemic on counties with higher self-employment shares and greater employment shares in all firm-size categories under 250 employees are negative, but they are always statistically insignificant. Because the negative-coefficient pattern applies in all 12 cases, with some almost statistically significant, there is weak evidence that concentrations of employment in small firms are associated with reductions in consumer spending in the early weeks and months of the pandemic. The effect on counties with higher shares of employment in firms with 250-499 employees is only statistically significant in the metro sample, suggesting that metro counties with higher employment shares in relatively large, small businesses did not fare as badly. Overall, the county's firm-size structure does not have appear to have a major effect in the local severity of the recession. These findings suggest that concentrations of small firms are not linked to greater economic resilience to the Covid shock, at least in immediate impact, which would contradict existing evidence of the positive role that small businesses play in promoting resilience. **(**Liang and Goetz, 2016; Tsvetkova, Partridge and Betz, 2019**).**

More populated counties experienced larger declines in aggregate spending during the pandemic, an effect driven by declines in more-populated nonmetro counties. Specifically, a one-standard deviation increase in county population in the pooled sample is associated with a 0.08 standard deviation decrease in consumer spending. The population effect is particularly large in nonmetro counties, where a one standard deviation population increase is associated with a 0.22 standard deviation decrease in consumer spending. In metro counties, the effect of a one-standard deviation population increase in population is negative but statistically insignificant. This result may seem surprising given the density in some of the largest American cities, but a key feature of larger rural communities is that they serve as a retail/service hub, operating as a central hub with more opportunities for Covid to spread in those communities. Also, larger rural communities would have been more likely to enforce business shutdowns than smaller rural communities.

A one-standard deviation increase in the share of high school dropouts and the share of high school graduates/individuals with some college experience (relative to the college-graduate share) was related to a 0.23 and 0.08 standard deviation change in consumer spending. One reason for this surprising result may be that spending by low-skilled workers was especially boosted by the $600 federal UI top-up. Another explanation could be that low-skilled workers were more prone to work in occupations deemed "essential" during the initial shutdown because those workers are disproportionately employed in delivery, grocery, or construction jobs. Nonetheless, this pattern runs counter to the typical recession in that less-educated workers are much more likely to be adversely affected than higher-educated workers.

Aggregate county-level consumer spending took a larger hit in metro counties with larger immigrant shares, which is consistent with Borjas and Cassidy's (2020) finding that immigrants face greater employment declines during the pandemic. Our results further indicate that counties with older pre-pandemic workforces saw greater declines in consumer spending relative to counties with more prime-aged workers. One possible explanation for this results is that older workers may have more fears about virus exposure and are less willing to leave their residence for shopping (and older residents may also be less comfortable shopping online).

5.2 Weekly Change in UI Claims

Our next results assess the pandemic's impact on county labor markets by examining changes in weekly UI claims after the national emergency declaration. The corresponding pooled-model results in column 4 of Table 2 indicate that weekly UI claims are more responsive to having larger leisure-services and manufacturing sectors—i.e., a one-standard deviation change in the employment shares of leisure services and manufacturing are respectively related to a 0.18 standard deviation and 0.11 standard deviation change in UI claims. The relatively larger effects for UI claims versus spending is reasonable given that unemployed leisure service or manufacturing workers typically received the $600 additional weekly UI PUA benefit, which supports greater household spending. The pandemic's effect for leisure services was felt in both metro and nonmetro counties, but the response was about 2.3 times larger in metro counties (0.300 vs. 0.129). In contrast, the COVID-19 manufacturing response was only significant for metro counties, and, even ignoring statistical significance, the point estimate for metro counties was about 5 times larger than for nonmetro counties. One reason for the metro/nonmetro discrepancy might be higher UI take-up rates in urban areas, perhaps related to larger urban firms providing more information on the CARES act provisions.

The results for the agriculture and mining sector are especially interesting. In the pooled sample, the agriculture and mining employment share is statistically insignificant. In contrast, it is positive and statistically significant in the metro sample and negative and significant in the nonmetro sample. The magnitude of the metro response is also about three-times larger than that of the nonmetro response. These patterns may be attributable to the fact that the types of agriculture and mining activities in rural and metro settings differ. There is typically more specialty farming near urban areas to provide local foods, where local-restaurant closings had a large effect. The "positive" nonmetro response likely relates to work on large rural farms typically use small workforces where workers are not usually in close proximity to each other.

In addition, it may be surprising that a one-standard deviation increase in metro-county public-sector employment generates a rather large, statistically significant -0.17 standard deviation decrease in weekly UI claims. Given that the effects for the pooled sample were significantly negative and rather small in size and that the nonmetro effect was insignificant and also small in magnitude, these findings may relate to public-sector jobs being slowly trimmed as the pandemic took hold.

Small businesses have reportedly struggled immensely during the pandemic, yet our results paint a decidedly more complex picture. For example, using the pooled sample, counties with higher shares of self-employed workers experienced a 0.23 standard deviation increase in UI claims. This effect is mainly driven by metro counties, in which a one standard deviation increase in the self-employment share is associated with a 0.60 increase in UI claims, by far the largest response for any variable. The nonmetro response is positive, though barely one-tenth of the size of the metro response and the coefficient is not significant at conventional levels. Of course, one key feature of the CARES Act is that self-employed workers became eligible for UI, which is a major change from past unemployment insurance policy. Thus, this positive response may reflect the extension of UI benefits to this previously ineligible group.

Counties with greater employment shares in firms with under 250 employees had less weekly UI claims on average. However, the negative response for the average employment share of firms with 20-49 employees was only statistically significant for nonmetro counties. Using the pooled sample, a one-standard deviation increase in the firm-size employment share for businesses with under 20 employees and between 50 to 249 employees is associated with a 0.13 and 0.07 standard deviation decrease in UI claims, respectively.[9] The corresponding responses for metro and nonmetro counties are also statistically significant for those two categories and of similar magnitude. The 20-50 employee firm-size employment-share coefficient is only statistically significant for nonmetro counties, with a relatively small response.

We expect that the firm-size results relate to two factors. First, for the smallest firms, employees may be less attached to the labor market and are not fully aware of UI programs, or they do not meet the minimum wage and work-tenure histories to qualify for benefits. Second, the firm-size results may be attributable to the launch of the Paycheck Protection Program (PPP). The PPP is a business loan program created by the CARES Act to help self-employed workers, sole proprietors, independent contractors, nonprofits, veteran organizations, and tribal businesses retain their workforce. So, instead of laying off workers, which increases UI claims, if PPP recipient firms maintain their workforce, a certain percentage of their loan is forgiven. This incentivizes firms to keep workers longer than they would otherwise, which could explain why increases in UI claims generally aren't seen for counties with high employment shares in firms that are typically eligible for PPP benefits.

In contrast, small businesses reportedly struggled to obtain loans from the PPP because of administrative hurdles, like long wait times due to banks prioritizing their biggest and best

[9] The employment share at firms with > 500 workers is the omitted category.

customers, and a fee structure favoring bank loans to the largest firms (Bartik et al., 2020; O'Connell et al., 2020). For example, the largest 5% of loans accounted for over 50% of the total funds dispersed in the PPP. These facts suggest that counties with large small-firm employment shares could see disproportionately large increases in UI claims, but our evidence of reductions in UI claims in counties with large small business employment suggests that these administrative hurdles may not have been as salient on average as previous studies suggest.

The response of UI claims to county-population differs from that for aggregate consumer spending. A one-standard deviation population increase is associated with a statistically significant 0.17 standard-deviation *decrease* in UI claims. The negative response is more consequential in metro counties (i.e., -0.22 vs. -0.14). Yet, population was associated with less consumer spending (especially in nonmetro settings) even while linked to less unemployment. It could be that fears of Covid infection drive consumer-spending reductions in more populated areas, conditional on income and/or employment status.[10] However, the additional $600 pandemic UI top-up from the CARES Act may have had such a positive effect on lower-income households that unemployed workers in many of those households earned more from UI than wages in their previous jobs. Fewer UI claims imply that many lower-income households have less income, leading to less spending—illustrating how the federal UI changes can produce unexpected impacts.

In the pooled, metro, and nonmetro samples, a one-standard deviation greater high-school graduate population share, including those with some college experience (but not college graduates), is associated with about a 0.20-0.23 standard-deviation decline in weekly UI claims. The high school dropout coefficient is statistically insignificant. Therefore, a surprising pattern

[10] This is consistent with Chetty et al. (2020) who show that decreases in spending were driven by higher-income households.

of the early stages of the Covid recession was the relative increase in UI claims in places with higher shares of college graduates.

These findings may be explained by the fact that less-educated workers are likely to be employed in jobs and sectors that are deemed essential and are therefore more able to retain their job amidst the pandemic (Montenovo et al., 2020). An alternative explanation is that more educated workers better understand the CARES Act's changes to UI and are better equipped to take advantage of its benefits. Nonetheless, as the consumer spending results show, counties with lower college-graduate shares had relatively higher levels of consumer spending amidst the pandemic, supporting the idea that less-educated workers are more likely to retain their jobs. If they do become unemployed, the UI-benefit top-up leads to relatively greater household-spending increases.

Using the pooled sample, a one-standard deviation change in the population shares of young (18-25) and older (55-65) workers decreased UI claims by a statistically significant 0.12 and 0.44 standard deviations on average, respectively, relative to the prime-age worker share. The response of "young workers" is primarily driven by metro counties, whereas the share of older workers in both metro and nonmetro counties had statistically significant reductions in UI claims. Young workers, especially those employed in low-skilled jobs such as warehousing or delivery, again may be more likely to be employed in jobs deemed "essential," or they would be less likely to file for unemployment insurance than prime-age workers. Older workers, on the other hand, are historically less likely to be fired during economic downturns because of labor hoarding (Johnson and Butrica, 2012). Indeed, as noted in the previous subsection, an older population is associated with greater reductions in consumer spending during the pandemic, consistent with the hypothesis that the fear of infection could be driving the response.

We find no differential effect of the Covid-19 pandemic on weekly UI claims in counties where immigrants make up a greater share of the population. Indeed, even as we find that counties with greater immigrant shares experience weaker economies, immigrants are less likely to claim UI. One explanation may be Trump Administration policies that penalize immigrants who use public welfare before applying for U.S. citizenship (Kannos-Young, 2020). Yet, we find that counties with larger shares of both young and old workers—relative to prime-aged workers—saw fewer weekly UI claims. This finding may relate to young workers being (1) more likely to work in “essential” sectors and therefore remain at work (Montenovo et al., 2020), (2) less attached to the labor market, meaning they are more likely to be ineligible for UI benefits, or (3) less likely to apply for benefits regardless of eligibility. Our finding that counties with older workforces have lower unemployment (all else equal) is consistent with findings from prior recessions, in which older workers benefit from seniority and are less likely to be laid off during economic downturns. However, this is inconsistent with Bui, Button, and Picciotti (2020), who find older workers experienced more adverse economic effects from the Covid-19 downturn.

5.3 Time Spent Away from Home and Time Spent at Work

Both the UI claims and aggregate consumer spending results paint similar pictures. For example, counties with relatively less-educated workforces experienced smaller increases in UI claims and greater increase in consumer spending relative to counties with larger college-educated shares. However, there are unexpected differences between how Covid-19 affected weekly UI claims and consumer spending, some of which indicate that UI claims are not always associated with lower income for the unemployed.

To better assess the competing explanations behind these results, we now examine two related indicators of economic activity: time spent away from home and time spent at work.

Table 3 shows the corresponding regression results for these outcomes. Generally, these results are consistent with the consumer spending and UI claims results and provide additional insight into some of the more unexpected results.

Counties with larger self-employed workforces experienced *increases* at time spent at work relative to counties with smaller self-employed workforces. On one hand, the CARES Act UI provisions allowed self-employed workers to draw UI benefits for the first time, which could result in less time spent at work, yet our time-at-work results suggest that counties with higher shares of self-employed workers had greater shares of their workforce spending time at the workplace. It is unclear from our findings whether self-employment promotes the resilience of local economies, increasing *overall* economic activity, or whether establishments owned by self-employed workers are simply remaining open (despite increases in UI claims).

The micro-firm employment share (for firms with under 19 employees) is negative and statistically significantly related to time spent at work, whereas it was negative and statistically significantly related to UI claims. The pattern is consistent with the hypothesis that the smallest firms were often forced to close and that fewer of their employees filed for UI.

One somewhat anonymous results presented above was that, all else equal, more-populated counties experienced relatively less consumer spending despite fewer UI claims. While one explanation is that more populated regions were initially hard hit by the pandemic, another explanation is that more-populated counties are related to fewer UI claims, and in turn, less disposable income for low-income households because they were not receiving the federal $600 top-up. However, the results in Table 3 suggest that in more populated areas, people spend less time at work, consistent with the hypothesis that employment declined in more populated areas despite corresponding reduction in UI claims.

Greater less-educated employment shares (less than a Bachelor's degree) is positively and statistically significantly related to increases in time at home and at work. This finding further supports the hypothesis that having a relatively less-educated workforce is positively linked to local economic activity with less-educated workers faring relatively well, at least early in the pandemic, all else equal. Given that we control for both industry composition and firm size, this result is less-supportive of the notion that the PPP program was the reason for less-educated workers faring better because the time-spent-at-work results apply regardless of the share of "small" firms benefitting from the PPP program.

We obtain similar findings for counties with young workforces—i.e., using the pooled sample, a one-standard deviation increase in the young-adult population share is associated with a 0.005 standard deviation increase in time spent at work, driven by metro counties. In contrast, having a greater share of older workers is positively related to time spent at work, though this pattern appears to be stronger in nonmetro counties. These results support the notion that older workers were less likely to draw UI, suggesting that they remained in the workforce, with their lower spending levels attributable to an unwillingness to shop in person or online. [Also, older rural workers may have been more skeptical of the severity of Covid and continued working, all else constant.]

Metro counties with higher immigrant worker shares also experience decreased time at home and work, consistent with the notion that immigrants especially face difficult challenges from the Covid recession. In another result that is inconsistent with past recessions, counties with greater Black population shares had a statistically significant positive relationship with time spent at work—further suggesting that Blacks were not disproportionately harmed by the Covid recession, all else constant.

5.4 Small Business Openings and Small Business Revenue

Overall, our results suggest that Covid had especially adverse effects on outcomes for small businesses. While the smallest existing businesses were more likely to close, it is important to understand the effects on the revenue of small business that stayed open and to understand how the pandemic affected the likelihood of new, small business to open. Further, the CARES Act and the resulting PPP program were supposedly targeted towards supporting small businesses, so examining the effect on the pandemic on outcomes for small businesses is important for understanding the effectiveness of these programs. As shown by the results in Table 4, unsurprisingly, counties with greater employment shares in leisure services experienced fewer small-business start-ups and decreased small-business revenue, and the magnitudes of the responses is rather large. In contrast, the county's manufacturing employment share is statistically unrelated to small-business revenues and start-ups. Finally, more populated counties experienced depressed small-business activity.

Interestingly, we find no statistically significant effect of the county's firm-size composition on small-business openings and revenue. This suggests that our prior finding that concentrations of employment in the smallest-sized firms is associated with depressed economic activity is probably due to small business closures (permanent or temporary) and not due to decreased start-up activity or reduced revenues for small firms that remain open. We do, however, find that both metro and nonmetro counties with greater pre-Covid self-employment shares experienced increased small-business openings and small-business revenue, indicating that self-employed workers may have been more likely than other workers to start (additional) new businesses during the pandemic (again, the magnitude of the self-employment coefficient is rather large, especially for metro openings). Another explanation for these positive effects could be that greater concentrations of self-employed workers support a stronger entrepreneurial climate that leads to a more dynamic and resilient small-business sector.

We continue to find that having a relatively less-educated workforce promoted economic activity during the pandemic, all else equal. Small-business revenue and openings were positively associated with greater population shares with less education, and the magnitudes are rather large). Lastly, we find that small-business revenue and start-ups in both metro and nonmetro counties are negatively related to their pre-pandemic shares of older workers. This finding may reflect general economic struggles for older workers due to greater concerns about the virus outside of the home, or perhaps from the general reluctance of older individuals to start new businesses, especially during uncertain times. Having a greater Black population share is statistically associated with more small business activity, which may reflect the relatively strong economies in some counties with large Black-population shares. Similarly, based on earlier findings that immigrants are associated with less robust economies during the pandemic, it is unsurprising that higher immigrant population shares are unrelated to small-business revenue.

5.5 Low-Income Employment and Earnings

One goal of the CARES act was to financially support low-skilled workers who are typically more vulnerable during economic downturns. Thus, Table 5 reports the results for how the pandemic affected the employment and earnings for low-income individuals, which should shed light on how effective the CARES act was in achieving its goal in the short term. We focus our discussion on low-income earnings because the low-income employment results are quite similar. Not surprisingly, the results suggest that low-income workers were adversely affected in counties with greater concentrations of employment in leisure services and manufacturing. Likewise, low-income workers suffered more in populated metro and nonmetro counties, consistent with our findings that more populated counties had more depressed local economies due to the pandemic.

As with aggregate consumer spending, we find slightly higher low-income employment and earnings in metro counties with greater employment shares in firms with 0-19 and 20-49 employees, respectively, but we find no statistically significant effects for firm employment shares for other size categories. Therefore, while the Covid recession struck the smallest firms in particular, the general importance of small businesses to low-income workers in metro counties indicate that this also adversely affected low-income workers. We did, however, find increases in low-income earnings and employment in metro counties with higher shares of self-employed workers, further supporting the idea that higher self-employment concentrations promote local resilience and aid in "protecting" low-income workers.

Low-income earners fare better in both metro and nonmetro counties with concentrations of high school graduates including those with some college experience, relative to counties with higher college-educated population shares. The results continue to support the notion that places with relatively low educational-attainment levels fared better during the initial stages of the Covid recession, counter to the trends exhibited during past recessions. Again, consistent with our previously reported results, declines in low-income employment and earnings were more pronounced in metro counties with higher immigrant population shares. Lastly, we find increases in low-income employment and earnings on average in counties with younger pre-pandemic workforces and declines in nonmetro counties with older pre-pandemic workforces.

6. Conclusion

The Covid pandemic is a unique opportunity to understand the effects of geographically widespread natural disaster that closes much of the economy. Existing research assessed how demographic groups, occupations, industries, regions responded to past recessions. This study's main contribution is to assess differences in the transmission of the Covid recession across local economies and to identify the characteristics that produced the economic patterns that differ substantially from those of previous recessions.

Using weekly, county-level data, we examined the pandemic's effects on local aggregate spending, UI claims, time-at-home and time-at-work, small-business openings and revenue, and low-income employment and earnings. Our findings do indeed indicate that the Covid recession's impacts varied from past recessions. For example, while local concentrations of manufacturing had the typical negative effects during this recession, the adverse role played by concentrations of leisure services was even larger. Likewise, greater population in both metro and nonmetro settings led to greater economic hardship, meaning agglomeration economies generally do not shield more populated areas from adverse economic effects during this pandemic. Furthermore, based on the regional resilience literature, a county's firm-size structure should play a positive role in mitigating the effects of an economic downturn, but its effects were ambiguous in our case. In particular, greater employment concentration in small firms was associated with fewer UI claims, but there were generally no other economic effects of firm-size structure except for reduced time at work—suggesting that relatively fewer UI claims may have more to do with fewer small-business employees qualifying for UI (or they were less knowledgeable about UI).

The responses to self-employment clearly showed how the federal $600 UI top-off affected behavior. Especially in metro areas, greater self-employment shares were associated with substantial increases in UI claims. Yet, consistent with the favorable role that self-employment plays in supporting local economic resilience, it was generally positively related to low-income employment/earnings, small business revenue/openings, and overall greater time at work, though these favorable responses were stronger in metro counties.

An unexpected finding was that having a greater population share of young adults was linked to fewer UI claims (and spending *more* time at work), while the other economic responses tended to be minimal. It is uncertain whether this pattern was due to young workers supplying businesses with labor for highly demanded services such as delivery, or whether it was attributable to young workers having less fears of Covid and consequently remaining in the workforce. By contrast, while locations with greater older-resident population shares generally experienced the expected reductions in UI claims and more time spent at work, the responses of the other economic outcomes tended to be negative, consistent with older workers spending less locally. Similarly, another unexpected finding was that having greater shares of less-educated residents was associated with more time at work and fewer UI claims and consistently positively related to aggregate spending, small-business performance, and low-income workers.

The Black population share also had an unexpected positive relation with UI claims but was associated with more time at work and positive outcomes for low-income workers (and some positive links to small-business performance). Greater immigrant shares were associated with weaker outcomes, especially in metro counties. In sum, compared to past recessions, the expected age, Black, and education effects were reversed, meaning that extrapolating from past recessions can produce misleading predictions when assessing recessions with different origins.

At the broader regional level, the sharp economic downturn and rapid upturn did not produce the expected regional patterns from past recessions, nor was there a consistent negative relationship with the severity the Covid outbreak with local economic activity. For one, manufacturing intensity did not play an outsized role in driving regional relationships. Second, leisure services had stronger effects, even after controlling for workforce characteristics. However, the $600 federal UI top-off appeared to affect local economic responses. For example, oddly, having more less-skilled and younger workforces was a positive attribute—in which a key factor seemed to be less fear of Covid infection and strong labor-market matches with "essential" economic activities. The result was a patchwork of regions that did relatively better than expected such as the Great Lakes and Plains states, while other regions such as California, Hawaii, and Oregon may have underperformed.

The results point to possible paths for future research. For example, the "nontraditional" demographic and industry findings indicate a great need in understanding how the $600 UI top-off and the PPP affected behavior (or perhaps in the latter case, did *not* affect behavior). This research needs to assess labor-market outcomes *and* spending behavior. Likewise, it is especially crucial to understand the role of supply-chain disruptions in producing these results. Indeed, this would have critical policy implications for understanding how industry composition affects local resilience to widespread national disasters. Finally, it remains to be seen whether past relationships will take hold as the Covid recession drags on.

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Figure 1: 2019-2020 Monthly U.S. Employment: February 2020 = 100, (Not Seasonally Adjusted)

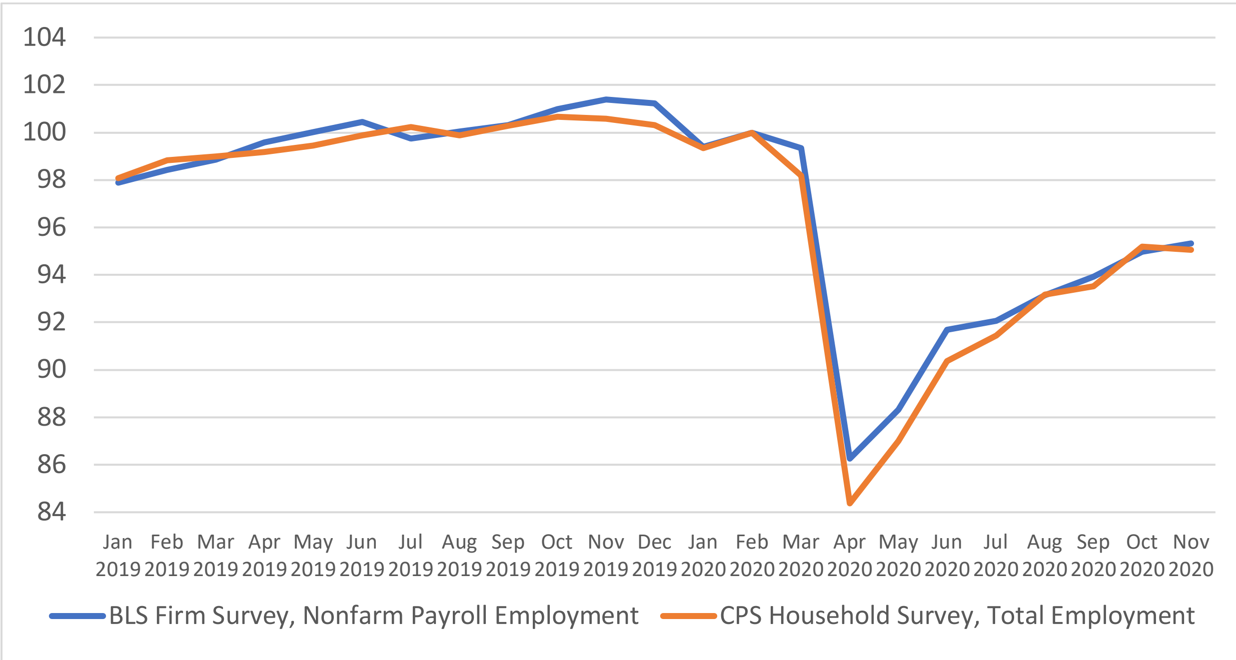

Figure 1a and 1b: State Nonfarm Employment Growth

Figure 1a: February 2020-April 2020

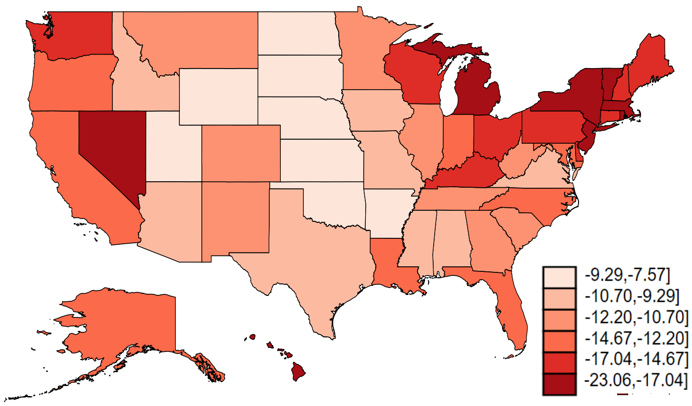

Figure1b: April 2020-October 2020

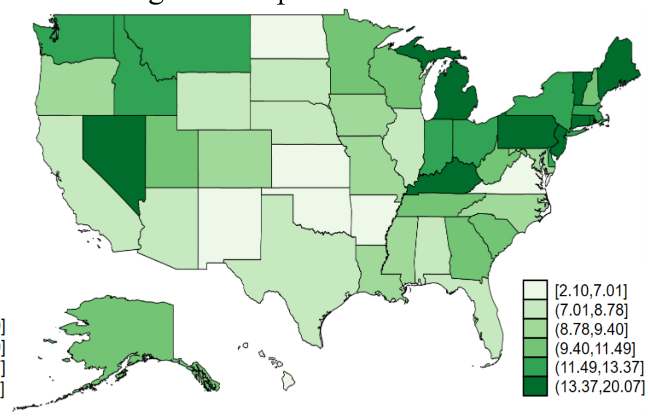

Table 1: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Dependent Variables					
Aggregate spending	221,544	-0.106	0.153	-0.809	0.372
Time spent away from home	67,719	-0.127	0.094	-0.391	0.0556
Time spent at workspace	155,605	-0.258	0.175	-0.724	0.143
Low income employment	236,448	-0.139	0.182	-0.991	1.05
Low income earning	236,448	-0.132	0.189	-0.992	2.47
Small business opening	227,181	-0.104	0.141	-0.797	0.192
Small business revenue	227,181	-0.075	0.247	-1	0.877
Unemployment Claims	23,558	5.775	12.035	-1	337.633
Independent Variables					
Agriculture and mining employment share	2,703	0.022	0.047	0	0.465
Manufacturing employment share	2,703	0.157	0.119	0	0.712
Leisure services employment share	2,703	0.127	0.066	0	0.934
Public service employment share	2,703	0	0.001	0	0.027
Self-employment share	2,703	0.106	0.037	0.027	0.312
Employment share at businesses with 0-19 employees	2,703	0.271	0.103	0.036	0.789
Employment share at businesses with 20-49 employees	2,703	0.118	0.04	0.016	0.342
Employment share at businesses with 50-249 employees	2,703	0.166	0.057	0.005	0.481
Employment share at businesses with 250-499 employees	2,703	0.062	0.045	0	0.432
Log population	2,703	10.579	1.313	7.09	16.128
High school dropout	2,703	0.132	0.06	0.012	0.485
High school graduates or some college experience	2,703	10.579	1.313	7.09	16.128
Black share	2,703	0.095	0.144	0	0.874
Hispanic share	2,703	0.091	0.132	0	0.991
Asian share	2,703	0.014	0.025	0	0.359
Other races share	2,703	0.059	0.068	0.002	0.833
Immigrants share	2,703	0.049	0.057	0	0.533
Young employment share	2,703	0.133	0.036	0.026	0.443
Old employment share	2,703	0.251	0.044	0.118	0.511

Table 2: Effects of Covid-19 on Consumer Spending and Unemployment Insurance Claims

	Aggregate spending (total)	Aggregate spending (metro)	Aggregate spending (nonmetro)	Increase in weekly UI claims (total)	Increase in weekly UI claims (metro)	Increase in weekly UI claims (nonmetro)
Industrial Composition						
COVID X Agriculture and mining employment share	0.0104	-0.0563	-0.00242	-0.0132	0.137**	-0.0450*
	(0.0276)	(0.0640)	(0.0311)	(0.0252)	(0.0660)	(0.0258)
COVID X Manufacturing employment share	-0.0822***	-0.00853	-0.124***	0.109***	0.261**	0.0514
	(0.0248)	(0.0340)	(0.0373)	(0.0386)	(0.1030)	(0.0326)
COVID X Leisure services employment share	-0.0566**	0.00442	-0.0789**	0.178***	0.300***	0.129***
	(0.0243)	(0.0336)	(0.0393)	(0.0377)	(0.0931)	(0.0424)
COVID X Public service employment share	0.0556	0.072	0.0659	-0.00466	-0.171***	0.0168
	(0.0396)	(0.0828)	(0.0434)	(0.0168)	(0.0533)	(0.0146)
Small Businesses and Self Employment						
COVID X Self-employment share	-0.00748	-0.0428	-0.0393	0.230***	0.604***	0.0756
	(0.0347)	(0.0492)	(0.0517)	(0.0491)	(0.1330)	(0.0494)
COVID X Employment share at businesses with 0-19 employees	-0.0349	-0.0447	-0.0272	-0.134***	-0.165*	-0.129***
	(0.0323)	(0.0456)	(0.0479)	(0.0396)	(0.0991)	(0.0322)
COVID X Employment share at businesses with 20-49 employees	-0.0388	-0.0647	-0.0333	-0.0227	0.0729	-0.0467*
	(0.0273)	(0.0443)	(0.0337)	(0.0277)	(0.0711)	(0.0268)
COVID X Employment share at businesses with 50-249 employees	-0.0208	-0.0152	-0.0241	-0.0651***	-0.107*	-0.0403*
	(0.0233)	(0.0401)	(0.0299)	(0.0239)	(0.0583)	(0.0238)
COVID X Employment share at businesses with 250-499 employees	0.00648	0.0627**	-0.0171	-0.012	-0.0464	-0.00235
	(0.0215)	(0.0293)	(0.0297)	(0.0208)	(0.0481)	(0.0202)
Population						
COVID X Log population	-0.0810***	-0.0405	-0.218***	-0.171***	-0.218**	-0.136**
	(0.0276)	(0.0347)	(0.0618)	(0.0510)	(0.0892)	(0.0611)
Education						
COVID X High school dropout share	0.229***	0.200***	0.234***	-0.0522	-0.00957	0.0113
	(0.0302)	(0.0400)	(0.0469)	(0.0424)	(0.1020)	(0.0423)
COVID X High school graduate and some college share	0.0775***	0.0590**	0.0645*	-0.225***	-0.234***	-0.200***
	(0.0196)	(0.0236)	(0.0382)	(0.0563)	(0.0901)	(0.0596)
Race and Ethnicity						
COVID X Black share	-0.0163	-0.0277	0.00313	0.115***	0.187***	0.0423
	(0.0195)	(0.0232)	(0.0354)	(0.0356)	(0.0603)	(0.0406)

COVID X Hispanic share	-0.0912***	-0.0622**	-0.107***	-0.205***	-0.393***	-0.0923
	(0.0238)	(0.0290)	(0.0393)	(0.0709)	(0.1320)	(0.0962)
COVID X Asian share	-0.0168	-0.00942	-0.181*	-0.0398	-0.164**	-0.0336
	(0.0183)	(0.0198)	(0.1000)	(0.0518)	(0.0810)	(0.1140)
COVID X Other races share	-0.0796***	-0.0803***	-0.0819**	-0.0106	-0.116	-0.015
	(0.0252)	(0.0285)	(0.0321)	(0.0248)	(0.1010)	(0.0183)
Immigrants						
COVID X Immigrants share	-0.101***	-0.126***	-0.0824	0.0102	0.225	-0.0929
	(0.0247)	(0.0313)	(0.0581)	(0.0916)	(0.1860)	(0.1120)
Age of Workforce						
COVID X Young employment share	-0.023	0.00876	-0.0377	-0.116***	-0.195***	-0.043
	(0.0200)	(0.0239)	(0.0331)	(0.0381)	(0.0629)	(0.0441)
COVID X Old employment share	-0.0796***	-0.0272	-0.0885*	-0.438***	-0.845***	-0.193***
	(0.0266)	(0.0335)	(0.0460)	(0.0672)	(0.1250)	(0.0587)
COVID	-0.181***	-0.239***	-0.192***	0.378***	0.517***	0.318***
	(0.0302)	(0.0506)	(0.0545)	(0.0346)	(0.1070)	(0.0420)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221,544	112,914	99,603	23,558	9,441	13,891
R-squared	0.523	0.634	0.443	0.465	0.486	0.489

Table 3: Effects of Covid-19 on Time Spent Away from Home and Time Spent At Work

	Time spent away from home (total)	Time spent away from home (metro)	Time spent away from home (nonmetro)	Time spent at workplace (total)	Time spent at workplace (metro)	Time spent at workplace (nonmetro)
Industrial Composition						
COVID X Agriculture and mining employment share	0.00363	-0.0312	-0.0573	0.00702***	0.0056	0.00630**
	(0.0372)	(0.0454)	(0.0684)	(0.0022)	(0.0045)	(0.0025)
COVID X Manufacturing employment share	-0.0771***	-0.0860***	-0.136***	-0.00642***	-0.00905***	-0.00703***
	(0.0180)	(0.0202)	(0.0338)	(0.0016)	(0.0022)	(0.0023)
COVID X Leisure services employment share	-0.00635	0.00139	-0.0757**	-0.0120***	-0.00836**	-0.0198***
	(0.0198)	(0.0248)	(0.0326)	(0.0021)	(0.0033)	(0.0026)
COVID X Public service employment share	0.00165	0.0675	-0.016	0.0000401	-0.000839	-0.00272
	(0.0189)	(0.0527)	(0.0158)	(0.0035)	(0.0059)	(0.0044)
Small Businesses and Self Employment						
COVID X Self-employment share	0.361***	0.394***	0.176***	0.0280***	0.0439***	0.0146***
	(0.0279)	(0.0306)	(0.0580)	(0.0026)	(0.0036)	(0.0036)
COVID X Employment share at businesses with 0-19 employees	-0.112***	-0.158***	0.0499	-0.0141***	-0.0193***	-0.00809**
	(0.0280)	(0.0312)	(0.0547)	(0.0026)	(0.0035)	(0.0037)
COVID X Employment share at businesses with 20-49 employees	-0.0286	-0.0065	-0.075	0.00309	0.00539*	0.00279
	(0.0285)	(0.0331)	(0.0593)	(0.0020)	(0.0029)	(0.0026)
COVID X Employment share at businesses with 50-249 employees	-0.0263	-0.0133	-0.0746**	0.0018	0.00162	0.00198
	(0.0219)	(0.0265)	(0.0344)	(0.0015)	(0.0024)	(0.0020)
COVID X Employment share at businesses with 250-499 employees	-0.0435*	-0.0682**	0.00911	-0.00224	0.000555	-0.00362*
	(0.0234)	(0.0274)	(0.0354)	(0.0016)	(0.0025)	(0.0019)
Population						
COVID X Log population	-0.123***	-0.0921***	-0.272*	-0.0227***	-0.0169***	-0.0226***
	(0.0210)	(0.0224)	(0.1410)	(0.0023)	(0.0031)	(0.0050)
Education						
COVID X High school dropout share	0.317***	0.343***	0.315***	0.0341***	0.0403***	0.0255***
	(0.0235)	(0.0254)	(0.0473)	(0.0023)	(0.0029)	(0.0030)
COVID X High school graduate and some college share	0.198***	0.211***	0.0922**	0.0315***	0.0330***	0.0259***
	(0.0129)	(0.0140)	(0.0362)	(0.0016)	(0.0019)	(0.0031)
Race and Ethnicity						
COVID X Black share	-0.00402	-0.0202	0.0368	0.0113***	0.00860***	0.0146***
	(0.0124)	(0.0136)	(0.0287)	(0.0013)	(0.0017)	(0.0020)

COVID X Hispanic share	-0.0693***	-0.104***	-0.0337	0.00537**	0.00049	0.00325
	(0.0221)	(0.0228)	(0.0680)	(0.0024)	(0.0027)	(0.0036)
COVID X Asian share	-0.00138	0.00201	-0.0842	-0.00272	-0.000462	0.00374
	(0.0115)	(0.0121)	(0.1160)	(0.0017)	(0.0017)	(0.0062)
COVID X Other races share	0.0152	0.0524	-0.0341	-0.0013	0.00189	-0.000149
	(0.0262)	(0.0344)	(0.0281)	(0.0023)	(0.0033)	(0.0028)
Immigrants						
COVID X Immigrants share	-0.145***	-0.153***	-0.0639	-0.0109***	-0.0156***	-0.000383
	(0.0186)	(0.0201)	(0.0846)	(0.0026)	(0.0030)	(0.0047)
Age of Workforce						
COVID X Young employment share	0.0692***	0.0737***	0.0786**	0.00509***	0.00647***	-0.000511
	(0.0099)	(0.0109)	(0.0342)	(0.0015)	(0.0018)	(0.0025)
COVID X Old employment share	-0.00185	-0.027	0.0779**	0.00604***	-0.000296	0.00658**
	(0.0183)	(0.0202)	(0.0364)	(0.0021)	(0.0026)	(0.0033)
COVID	-0.882***	-0.932***	-0.682***	-0.230***	-0.232***	-0.222***
	(0.0287)	(0.0361)	(0.1180)	(0.0019)	(0.0033)	(0.0029)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,719	56,781	8,954	155,605	79,442	70,675
R-squared	0.965	0.968	0.952	0.952	0.968	0.932

Table 4: Effects of Covid-19 on Small Business Openings and Revenue

	Small business openings (total)	Small business openings (metro)	Small business openings (nonmetro)	Small business revenue (total)	Small business revenue (metro)	Small business revenue (nonmetro)
Industrial Composition						
COVID X Agriculture and mining employment share	0.0595*	0.0937*	0.0534	0.00263	0.00365	0.00175
	(0.0307)	(0.0559)	(0.0372)	(0.0309)	(0.0648)	(0.0367)
COVID X Manufacturing employment share	-0.0057	-0.0111	-0.0148	0.023	-0.00549	0.0327
	(0.0218)	(0.0308)	(0.0320)	(0.0253)	(0.0379)	(0.0366)
COVID X Leisure services employment share	-0.153***	-0.104***	-0.232***	-0.215***	-0.225***	-0.243***
	(0.0301)	(0.0343)	(0.0398)	(0.0268)	(0.0411)	(0.0387)
COVID X Public service employment share	-0.0131	0.0584	-0.0551	0.0147	0.0071	0.000468
	(0.0478)	(0.0881)	(0.0499)	(0.0427)	(0.0855)	(0.0515)
Small Businesses and Self Employment						
COVID X Self-employment share	0.207***	0.319***	0.161***	0.113***	0.192***	0.0551
	(0.0370)	(0.0488)	(0.0556)	(0.0376)	(0.0535)	(0.0583)
COVID X Employment share at businesses with 0-19 employees	-0.00787	-0.0684	0.018	0.0532	0.037	0.0528
	(0.0364)	(0.0487)	(0.0534)	(0.0373)	(0.0559)	(0.0511)
COVID X Employment share at businesses with 20-49 employees	-0.0208	-0.00749	-0.00389	-0.031	-0.054	-0.00395
	(0.0310)	(0.0432)	(0.0423)	(0.0312)	(0.0480)	(0.0420)
COVID X Employment share at businesses with 50-249 employees	-0.0209	-0.0672*	-0.00619	-0.00806	-0.0124	-0.0145
	(0.0225)	(0.0370)	(0.0280)	(0.0244)	(0.0416)	(0.0321)
COVID X Employment share at businesses with 250-499 employees	-0.0203	-0.00642	-0.0257	0.0225	0.0596	-0.00169
	(0.0228)	(0.0337)	(0.0309)	(0.0267)	(0.0452)	(0.0339)
Population						
COVID X Log population	-0.173***	-0.187***	-0.173**	-0.126***	-0.105***	-0.143*
	(0.0265)	(0.0348)	(0.0743)	(0.0287)	(0.0381)	(0.0757)
Education						
COVID X High school dropout share	0.113***	0.160***	0.027	0.179***	0.194***	0.103**
	(0.0277)	(0.0378)	(0.0407)	(0.0292)	(0.0434)	(0.0444)
COVID X High school graduate and some college share	0.0610***	0.0672***	0.0107	0.0883***	0.114***	0.0195
	(0.0190)	(0.0242)	(0.0428)	(0.0209)	(0.0268)	(0.0436)
Race and Ethnicity						
COVID X Black share	0.0667***	0.0145	0.126***	0.0472**	-0.0048	0.114***
	(0.0170)	(0.0217)	(0.0281)	(0.0213)	(0.0247)	(0.0371)

COVID X Hispanic share	0.0163	-0.0179	0.0177	0.0211	-0.0222	0.0553
	(0.0251)	(0.0312)	(0.0463)	(0.0267)	(0.0313)	(0.0569)
COVID X Asian share	-0.028	-0.0258	-0.0543	0.0314*	0.0332	-0.0357
	(0.0187)	(0.0210)	(0.0863)	(0.0189)	(0.0221)	(0.0808)
COVID X Other races share	0.0199	0.0229	0.0374	0.0212	0.0391	0.0249
	(0.0233)	(0.0322)	(0.0280)	(0.0193)	(0.0301)	(0.0241)
Immigrants						
COVID X Immigrants share	-0.0262	-0.0328	0.0186	-0.138***	-0.128***	-0.148**
	(0.0260)	(0.0314)	(0.0645)	(0.0277)	(0.0364)	(0.0740)
Age of Workforce						
COVID X Young employment share	0.0314**	0.0147	0.0196	0.0262	0.0243	0.0102
	(0.0158)	(0.0212)	(0.0265)	(0.0187)	(0.0244)	(0.0315)
COVID X Old employment share	-0.194***	-0.245***	-0.193***	-0.163***	-0.192***	-0.171***
	(0.0318)	(0.0370)	(0.0479)	(0.0309)	(0.0393)	(0.0519)
COVID	-0.663***	-0.560***	-0.688***	0.130***	0.102*	0.186***
	(0.0288)	(0.0472)	(0.0479)	(0.0342)	(0.0545)	(0.0549)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	227,181	115,871	103,358	227,181	115,871	103,358
R-squared	0.755	0.829	0.681	0.409	0.522	0.312

Table 5: Effects of Covid-19 on Low-Income Earnings and Employment

	Low-income earnings (total)	Low-income earnings (metro)	Low-income earnings (nonmetro)	Low-income employment (total)	Low-income employment (metro)	Low-income employment (nonmetro)
Industrial Composition						
COVID X Agriculture and mining employment share	-0.018	-0.0584	0.00829	0.0514	0.0192	0.0768*
	(0.0485)	(0.0470)	(0.0622)	(0.0386)	(0.0588)	(0.0463)
COVID X Manufacturing employment share	-0.159***	-0.109***	-0.196***	-0.109***	-0.0574**	-0.147***
	(0.0236)	(0.0309)	(0.0362)	(0.0218)	(0.0286)	(0.0330)
COVID X Leisure services employment share	-0.176***	-0.162***	-0.190***	-0.180***	-0.175***	-0.198***
	(0.0254)	(0.0301)	(0.0388)	(0.0241)	(0.0318)	(0.0354)
COVID X Public service employment share	-0.0774**	0.00396	-0.0957**	-0.019	0.0671	-0.0374
	(0.0386)	(0.0704)	(0.0448)	(0.0400)	(0.0590)	(0.0439)
Small Businesses and Self Employment						
COVID X Self-employment share	0.0629*	0.129***	0.0632	0.0580*	0.123***	0.0475
	(0.0361)	(0.0415)	(0.0604)	(0.0339)	(0.0390)	(0.0548)
COVID X Employment share at businesses with 0-19 employees	0.00114	0.0564	-0.022	0.0181	0.0817**	-0.0142
	(0.0362)	(0.0417)	(0.0542)	(0.0344)	(0.0415)	(0.0500)
COVID X Employment share at businesses with 20-49 employees	0.0405	0.0790**	0.0214	0.0257	0.0571	0.0117
	(0.0297)	(0.0400)	(0.0409)	(0.0297)	(0.0399)	(0.0403)
COVID X Employment share at businesses with 50-249 employees	0.0111	-0.00684	0.0148	-0.00151	-0.0243	0.00857
	(0.0242)	(0.0299)	(0.0332)	(0.0214)	(0.0302)	(0.0281)
COVID X Employment share at businesses with 250-499 employees	-0.0376	-0.00951	-0.044	-0.0197	0.00508	-0.0255
	(0.0247)	(0.0339)	(0.0340)	(0.0226)	(0.0332)	(0.0300)
Population						
COVID X Log population	-0.136***	-0.0895***	-0.154**	-0.136***	-0.0697**	-0.229***
	(0.0271)	(0.0321)	(0.0777)	(0.0247)	(0.0301)	(0.0711)
Education						
COVID X High school dropout share	0.0501*	0.0232	0.0892*	0.0531**	0.0224	0.105***
	(0.0287)	(0.0339)	(0.0471)	(0.0256)	(0.0316)	(0.0400)
COVID X High school graduate and some college share	0.0773***	0.0715***	0.127***	0.0589***	0.0672***	0.0843**
	(0.0185)	(0.0197)	(0.0449)	(0.0168)	(0.0182)	(0.0395)
Race and Ethnicity						
COVID X Black share	0.0500***	0.0389**	0.0720***	0.0369***	0.0322**	0.0413*
	(0.0153)	(0.0157)	(0.0270)	(0.0140)	(0.0151)	(0.0242)

COVID X Hispanic share	0.0689*	0.0709***	0.0215	0.0483	0.0661***	-0.0244
	(0.0369)	(0.0257)	(0.0881)	(0.0308)	(0.0244)	(0.0693)
COVID X Asian share	0.0189	0.0096	0.166	0.0129	0.0083	0.167*
	(0.0232)	(0.0165)	(0.1140)	(0.0205)	(0.0165)	(0.0885)
COVID X Other races share	0.0317**	0.0222	0.0371**	0.0276*	-0.00736	0.0394**
	(0.0148)	(0.0255)	(0.0187)	(0.0144)	(0.0223)	(0.0181)
Immigrants						
COVID X Immigrants share	-0.0600*	-0.0877***	0.0247	-0.0447	-0.0799***	0.0536
	(0.0330)	(0.0264)	(0.1010)	(0.0295)	(0.0270)	(0.0821)
Age of Workforce						
COVID X Young employment share	0.0450***	0.0288	0.0571*	0.0322**	0.0102	0.0485*
	(0.0164)	(0.0181)	(0.0293)	(0.0153)	(0.0174)	(0.0267)
COVID X Old employment share	0.0234	-0.0855***	0.0987*	0.0071	-0.111***	0.107**
	(0.0315)	(0.0287)	(0.0591)	(0.0289)	(0.0288)	(0.0514)
COVID	-1.281***	-1.298***	-1.223***	-1.561***	-1.591***	-1.477***
	(0.0347)	(0.0408)	(0.0614)	(0.0316)	(0.0416)	(0.0507)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	236,448	118,800	109,008	236,448	118,800	109,008
R-squared	0.583	0.776	0.464	0.676	0.832	0.565