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Lessons from the 2020 Covid recession for understanding regional resilience

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Abstract

The 2020 Covid-19 recession differs from past recessions due to the immediate economic collapse, making it a unique setting in which to assess local economic resilience. Using county-level data, we identify initial effects of the pandemic and accompanying stay-at-home orders on consumer spending, unemployment insurance claims, small businesses, and low-income employment and earnings. We discuss heterogeneity related to pre-pandemic county characteristics and find differences compared to past recessions. Counties with larger leisure services employment shares fared worse, while counties with less-educated, younger workforces fared better. We find an ambiguous role of small businesses in contrast with favorable impacts during prior downturns.

KEYWORDS

Covid-19, regional resilience

1 | INTRODUCTION

The 2020 Covid-19 pandemic created a global health crisis not seen since the Spanish Flu a century ago. As of late September 2021, Worldometer recorded over 4.7 million global deaths from Covid-19, including over 700,000 in the United States, the hardest hit country.[1] At its peak in late 2020 and early 2021, US daily mortality from Covid routinely exceeded 3000.

[1]Total US Covid deaths exceed the total of all American military war deaths since the Civil War. Brazil had the second most deaths at 592,000 [https://www.worldometers.info/coronavirus/].

Covid-19 was first detected in Wuhan, China in late 2019. The first confirmed US cases occurred in January 2020, although later analysis found that Covid was circulating in the United States in December 2019.[2] US cases exploded in March 2020, and President Trump's March 13, 2020 national emergency declaration led to a cascade of nonessential business shutdowns across most US states by the end of March. Even where shutdowns were not enforced, Covid fears led to plunges in economic activity.

Illustrating the disaster's scale, Figure 1 shows two measures of total US employment benchmarked to February 2020 = 100. Between February and April 2020, as the economy closed, US employment fell by 16% using the more inclusive household survey or by 14% using the Bureau of Labor Statistics (BLS) firm survey—that is, a remarkable 24.7 million jobs lost using the household survey.[3] This pain also includes the corresponding 4.3 to 10.9 million-worker increase in those employed part-time due to economic conditions.[4] Such a rapid US economic calamity has never occurred.[5]

Figure 2 illustrates the large spatial differences in nonfarm state job 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 the District of Columbia to Michigan's 20.1%. Economic activity collapsed in the Covid-ravaged Northeast through April–May, as it did in tourist destinations such as Nevada and Hawaii. While tourist locals typically struggle during recessions, their downturn is usually delayed until the recession matures, but here, negative effects were seen almost immediately.[6] In contrast, Great Lakes states usually lead the country into recession due to their manufacturing intensity, as households cut large durable-goods purchases and businesses limit investment (Partridge & Rickman, 2002). Yet, in this case, Great Lakes states initially performed near the US average. During the initial recovery, there are clear cases of reversion to the mean as in "typical" recoveries, such as the rapid recovery of hard-hit Michigan and Nevada or the relatively small bounce-back in the less-hit Plains states. However, hard-hit states such as Hawaii, some Northeast states, and California do not simply revert to the mean, while Kentucky's strong initial performance is an outlier.

The objective of this study is to assess factors that enhanced local economic resilience to the Covid recession by examining the recession's depth and unusual spatial transmission across regions. The aim is to identify characteristics that either mitigated or exacerbated the recession's initial impacts. The key factor underlying our analysis is that the intervening role of the local economy's structure varied considerably from past recessions. A related aim is to appraise how federal stimuli affected these spatial effects. These policies were striking for their novelty, rapid execution, and their grand scale compared to downturns since the Great Depression.

In assessing the dramatic Covid-19 economic shutdown, it is important to understand how it differed from past recessions. As will be seen, the unusual economic transmission across regions and sectors led to interdependent responses, producing effects that cannot be explained by examining basic aggregate indicators such as consumer spending or unemployment. For one, demographic groups experienced the Covid recession in unexpected ways. Likewise, the diffusion process via the local occupational and industry structures was unusual, including the key role

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

[3]The figure first reports nonfarm payroll employment, which is viewed as more accurate than other measures because it is based on a firm survey but does not include self-employed, farm workers or count 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 initial effects of Covid.

[4]For perspective, the BLS estimated that the total civilian labor force was 160.5 million in February 2020. 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.

[5]In the first two months of the Great Recession, nonfarm employment declined only 0.1%, and even at the employment trough, the firm survey reported a decline of only 6.3% and the household survey showed a 5.6% decline. In the Great Depression, for the first *two years* after September 1929s peak, nonfarm employment declined 19.2%. The decline in nonfarm employment from the Great Depression's September 1929 peak to its trough in March 1933 was 33.9%—that is, 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, US Vintage: 2005-08-01, Millions of Persons, Monthly, Not Seasonally Adjusted, NBER, Series #M0868AUSM148NNBR_20050801. [https://alfred.stlouisfed.org], December 18, 2020.

[6]Consistent with the standard pattern, Florida, also a tourist destination, initially avoided much of the initial plunge, likely due to fewer Covid-based restrictions than elsewhere during peak Spring Break season.

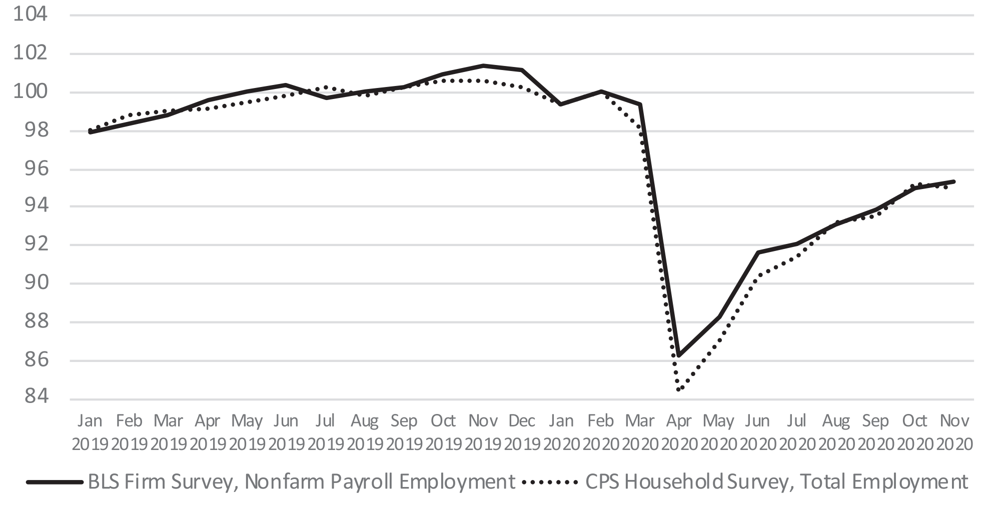

FIGURE 1 2019–2020 Monthly US employment: February 2020 = 100 (not seasonally adjusted). *Source*: Bureau of Labor Statistics and Current Population Survey

played by lower skilled "essential" occupations. Finally, individuals and businesses responded to novel federal policies in ways that produced atypical labor-force and firm responses. In sum, to fully appraise the resilience implications of the Covid recession, we will examine a wide range of economic outcome measures.

Standard recessions typically begin in certain sectors and regions due to factors such as asset-valuation "bubbles" popping, financial crises, or demand or supply shocks—for example, monetary policy mistakes or oil price shocks. Like a natural disaster, the Covid outbreak immediately halted economic activity across all sectors. Yet, this pandemic differs from natural disasters because its effects were not localized, it affected the entire nation and much of the world. Natural disasters have their sharpest supply chain effects for inputs that originate from nearby areas affected by the disaster, but this pandemic led to massive supply chain disruptions on national and global scales. Given that climate change may increase the likelihood of pandemics and the frequency and scale of natural disasters, appraising the Covid recession is useful for understanding resilience, especially given the execution of novel policy measures.

Our first contribution is to empirically assess the local severity of the Covid recession and identify *how* and *why* this recession differed from past downturns. The main goal is to identify the local factors associated with regional resilience. We find that, unlike previous recessions, counties with higher employment shares in the arts, entertainment, recreation, accommodation, and food services (which we call leisure services) were adversely affected, as were more populated counties, indicating that agglomeration economies were less effective in buffering populous counties when people were isolated. In addition, we found ambiguous effects of the county's firm-size structure on economic activity, which contrasts with the literature documenting the positive role that small businesses play in shielding areas from adverse shocks. Finally, on a positive note, counties with less-educated and younger workforces initially fared relatively well, likely because those workers are disproportionately employed in occupations deemed "essential," or perhaps they were less concerned about adverse health effects and remained in the workforce.

The next section of the paper discusses the relevant Covid-19 economic literature. The following sections discuss the data and empirical implementation. In particular, we describe our use of high-frequency US county-level data. We then present our empirical results, focusing on aggregate county-level economic conditions and related impacts on vulnerable low-income workers, and assess the critical effects on small business start-ups that shape

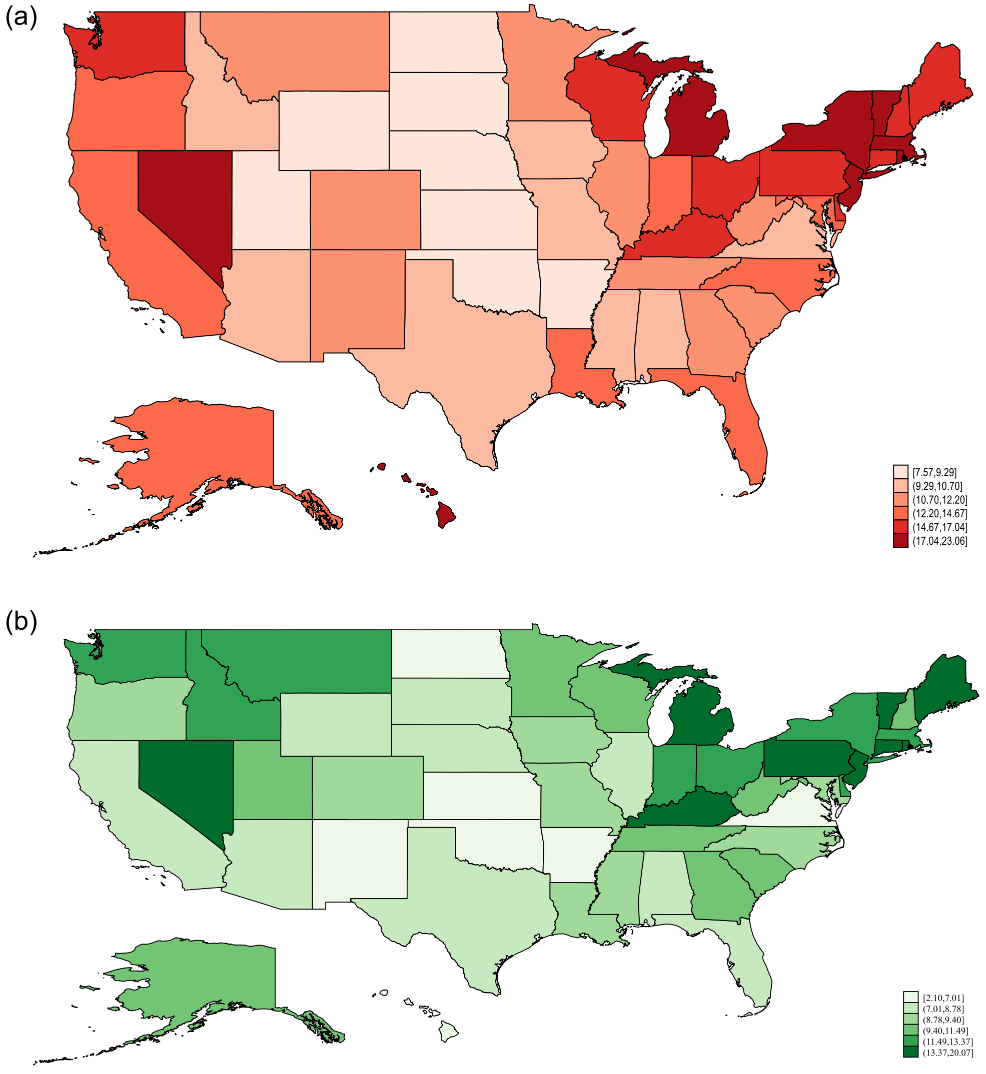

FIGURE 2 State nonfarm employment growth. (a) February 2020–April 2020. (b) April 2020–October 2020. *Source*: Bureau of Labor Statistics [Color figure can be viewed at wileyonlinelibrary.com]

future economic expansions. We then follow with a concluding discussion of the study's implications and suggest future research paths.

2 | LITERATURE REVIEW

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

2.1 | Heterogenous effects by industry and occupation

The first group of studies seeks to identify the industries and occupations most impacted by the Covid-19 pandemic in the United States. Using big data on US job-vacancy postings, Campello et al. (2020) find larger hiring declines for jobs defined as high-skill (e.g., CEOs, lawyers, postsecondary teachers, statisticians, and physicians) relative to low-skill jobs (e.g., farming, food services, landscaping, garment, and logging workers). The authors note that this finding is unexpected because less-skilled workers typically suffer more during a recession (Hershbein & Kahn, 2018). The authors explain this finding by citing reports of expedited hiring into low-skill occupations early in the pandemic (Gelles & Corkery, 2020).

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. Leisure and hospitality services and "nonessential" retail sectors fared the worst, and "essential" retail fared 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, Lozano Rojas et al. (2020) identify the economic effects of specific mitigation policies enacted by local governments and find that large increases in UI claims in late March 2020 occurred for almost all sectors and in all states. Similar to Forsythe et al. (2020), Lozano Rojas et al. (2020) conclude that the economic disruption was caused primarily by the virus-induced health shock and not by local mitigation policies aimed at stopping its 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 noncritical industries, suggesting that essential businesses had less severe job losses than those for non-essential businesses.

2.2 | Heterogenous effects by worker characteristics

The second subset of related Covid-19 studies examines the 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. They find larger employment declines in April and May 2020 among Hispanics, young workers, and those with a high school degree 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, Couch, 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 higher employment concentrations in occupations 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 helped partially protect them.

Papanikolaou and Schmidt (2020) find higher probabilities of nonemployment among women and lower-earning workers, with the largest adverse effects for females without a college degree and with young children.

Bui et al. (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%, compared with 13% among workers aged 22–44. 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 tasked with helping their children with online schooling, hence the nickname for the Covid recession: the "She-cession."[7] Finally, Borjas and Cassidy (2020) use monthly CPS data to assess how the pandemic affected immigrant workers relative to natives. They find that immigrant males 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 other studies, Cheng et al. (2020) did not examine how the pandemic and subsequent economic shutdown affected specific groups of workers. Instead, they considered how business *reopenings* in early summer 2020 differentially impacted various worker groups. 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, men, non-Hispanic whites, and prime-aged individuals were all less likely to be unemployed during the pandemic. Moreover, conditional on being unemployed, they were also more likely to be reemployed when businesses reopened.

2.3 | Effects on small businesses

The final subset of relevant studies discusses how the Covid-19 pandemic affected small businesses. Many of the studies directly surveyed small businesses for a better understanding of the unique effects of the pandemic. For example, Bartik et al. (2020) surveyed more than 5800 US small businesses in late March 2020, finding 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, Neilson et al. (2020) surveyed 8000 small business owners in late March and early April 2020, finding similar bleak expectations and that the smallest businesses had the least knowledge of CARES Act assistance programs. They conclude that small businesses may have lost funding from the Paycheck Protection Program (PPP) because of having less information than larger firms.

Alekseev et al. (2020) use 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—for example, 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% of small business respondents reduced the number of active employees, which is consistent with Campello et al. (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% between February and April 2020 with losses across almost all

[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].

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 et al. (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 6–50 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 3100 US counties (or equivalents), which we divide into metropolitan and nonmetropolitan subsamples using US Census Bureau definitions.[8] Our dependent variables are defined as follows, using the UI claims outcome variable to demonstrate:

$$\Delta UI_{ct} = (UI_{ct} - AvgUI_{cb})/AvgUI_{cb},$$

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.[9] This variable is defined for the week of January 11, 2020 through the week of July 4, 2020. As described below, some of our dependent variables are defined daily, not weekly. In these cases, t represents a given day, and the baseline period is defined as an average over days, not weeks. The specific days serving as the baseline period depend on data availability and are described in more detail below.

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 on 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.

[8]A description of these definitions is available here: https://www.census.gov/programs-surveys/metro-micro/about.html.

[9]We are demeaning our UI claims variable in the sense that we are calculating the percentage difference from the base period, in which the numerator takes the difference of the current period from the base period. The UI claims variable is defined in this manner to mirror the remaining dependent variables used in our analyses (discussed below), which were constructed by Chetty et al. and reported relative to a similar base period.

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 are 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 to February 6, 2020 average.

The dependent variables typically span the January 1, 2020 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), which expired on 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 concluding the sample period on June 30, 2020 allows us to avoid the vexing empirical problem of accounting for the second surge in Covid infections beginning in July 2020, as well as a third wave in 2021.

3.2 | Explanatory variables

We decided to include the following explanatory variables in our model after examining the relevant regional resilience, 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 for understanding how counties adapt and grow during recessions, and thus, is a key factor in the locale's resilience (Partridge & Tsvetkova, 2020; Tsvetkova et al., 2019). For example, manufacturing historically plays an outsized role in determining the regions that 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 shutdowns, whereas the past resilience literature has emphasized their positive effects (e.g., Liang & Goetz, 2016). Specifically, we include variables with the share of the county's employment in firms belonging to each of the following four size categories: 0–19 employees, 20–49 employees, 50–249 employees, and 250–499 employees.[10]

Next, we include variables describing the county's population and workforce. Population size is included because of its importance for agglomeration and growth (Martin & Ottaviano, 2001). Also, at least initially, Covid spread faster in larger cities, so there is a reason to expect differential economic impacts of the pandemic related to population size. We include educational-attainment measures due to the role human capital plays in attracting fast-growing, skill-intensive industries (Glaeser & Saiz, 2003) and its positive impact on future regional human capital levels (Chung & Partridge, 2019; Chung et al., 2020). Hence, we expect that educational attainment will be positively related to local resilience. 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 et al., 2013; Lewis & 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 and high school graduates plus those with some college experience, with the share having a bachelor's

[10]The omitted variable, therefore, is the employment share at firms with 500 or more employees.

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 made up by self-employed workers.

The employment data from the US Census Bureau's County Business Patterns (CBP) are used to identify pre-pandemic industry employment shares for each county. Because CBP county/industry data are often suppressed for confidentiality reasons, we use CBP data from the W.E. Upjohn Institute for Employment Research that estimates the suppressed values (Bartik et al., 2018) using an algorithm from Isserman and Westervelt (2006). From these data, we compute the 2016 total employment shares in the following industries: arts, entertainment, recreation, accommodation and food services (which we refer to together as leisure services); manufacturing; agriculture, mining, fishery, and forestry (which we refer to together as agriculture and mining); and public service.

We use the US 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 categories: 0–19, 20–49, 50–249, 250–499, and greater than or equal to 500 employees. We use data from the fourth quarter of 2017 for all states except South Dakota because it was the latest available data at the time of the analysis. We use data from the fourth quarter of 2016 for South Dakota because 2017 data are unavailable.

We standardize all dependent and independent variables by subtracting 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 pandemic helps us identify its effect, as well as the effects of accompanying stay-at-home orders on US county economic outcomes. Following the President's March 13, 2020 emergency declaration, US economic activity plummeted as "nonessential" businesses closed. Yet, the spatial magnitude of the collapse varied, 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 subsequent economic decline, we regress the 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 described above. The sizes of the estimated interaction coefficients measure how the pandemic's economic impact changes with respect to each county characteristic, conditional on all others.

Our model is similar to the generalized first-difference models employed by Duranton and Turner (2011), Duranton (2016), and Tsvetkova and Partridge (2016). The model starts with the dependent variables—that is, the percent change in the outcome variable relative to the county-average of the outcome variable (see Section 3.1). The differencing form we use for the dependent variable is akin to panel fixed-effect models because it differences out the county mean of the dependent variable. With dependent variable Y, we can write the following equation:

$$Y_{ist} = \alpha + \theta COVID_t + \delta_s + \mu_t + \varepsilon_{ist}. \tag{1}$$

The model in Equation (1) is the county-mean differenced dependent variable regressed on state and time fixed effects. The dependent variable can further vary by state (δ_s), time period (μ_t) with t being day or week), and a further shift variable indicating when Covid strikes. Duranton and Turner (2011) and Duranton (2016) argue that differencing models like Equation (1) may over-simplify the economic-adjustment process due to persistent disequilibrium effects that affect the adjustment process. Such disequilibrium factors relate to pre-existing structural conditions—e.g., manufacturing intensity because the industry is more unionized and has larger firms. Thus, they generalized their model by including initial values of key variables, as well as deep lags of other variables, which in our case, allows us to consider whether these structural characteristics affect how Covid impacts the local economy. If these additional variables are insignificant, the simpler difference model sufficiently reflects the economic adjustment process. If significant, the local economy is likely in disequilibrium, which seems probable during a pandemic.

We then estimate the following augmented econometric Equation (2):

$$Y_{ist} = \alpha + \sum \beta_j COVID_t * A_{isj} + \sum \gamma_j A_{isj} + \delta_s + \mu_t + \varepsilon_{ist}, \tag{2}$$

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 one, states manage their UI insurance program, and they set benefit levels and eligibility requirements (except for ad hoc federal assistance, including Pandemic Unemployment Assistance (PUA), allowing "gig" workers to draw UI, and the federal \$600 (or later, \$300) PUA top-up). States also use different state UI computer systems. States with the most antiquated software saw a collapse of their UI system for several weeks or more, leading to multiple UI filings by the same individual and lengthy delays before receiving benefits.[11]

We include *day* or *week* fixed effects, μ_t (e.g., when weekly UI claims are the dependent variable, μ_t are weekly fixed effects), to control for national effects common to all counties to eliminate bias from unobservables that change over time but are constant across counties. Examples include seasonal (i.e., monthly and/or quarterly) and national cyclical effects. Finally, for all j = 1…19, β_j is our coefficient of interest, which measures the changing effects of A_j due to structural shifts from the pandemic and from differing pre-pandemic levels of A_j. Standard errors are clustered at the county level.

β_j can be interpreted as the causal effect of the pandemic on local economic activity due to differing pre-pandemic levels of A_j if the following assumption holds: the error term is uncorrelated with unobserved, time-varying determinants of economic outcomes during early stages of the pandemic. This assumption is violated if there are time-varying, county-specific shocks that are both unobserved and correlated with local economic outcomes during the pandemic, like, for example, if local governments implemented policies to offset pandemic economic effects before March 2020. We believe this is extremely unlikely because the pandemic's severity was unanticipated and largely unknown in January 2020, our base month.

Further concerns about possible county-level, time-invariant fixed effects are mitigated by the construction of the dependent variable. Specifically, we divide changes in each economic outcome by the January 2020 base level of that outcome before the pandemic. This derivation means any remaining time-invariant county effects (not captured by state or year fixed effects or the A_j control variables) are in both the numerator and denominator of the dependent variable, and, consequently, cancel out. Thus, *at least in terms of the dependent variable*, county fixed effects are removed. The model also controls for key pre-pandemic socioeconomic conditions, further reducing the probability that omitted variables tangibly affect the results.[12] The descriptive statistics for the key variables are reported in Table 1.

[11]The GAO (2020) found that reported weekly UI Claims were overestimated for the early months of the pandemic. The GAO stated 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).

[12]To test the robustness of our results to the model's specification, we estimated alternative models using aggregate spending and UI claims as dependent variables. In this model, county fixed effects are now included and the non-interacted pre-pandemic covariates are omitted (and the state fixed effects are also omitted). The results, which are available upon request, are analogous to those discussed in Section 5, further confirming that unobserved time-invariant county characteristics are not driving our results.

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	2703	0.022	0.047	0	0.465
Manufacturing employment share	2703	0.157	0.119	0	0.712
Leisure services employment share	2703	0.127	0.066	0	0.934
Public service employment share	2703	0	0.001	0	0.027
Self-employment share	2703	0.106	0.037	0.027	0.312
Employment share at businesses with 0–19 employees	2703	0.271	0.103	0.036	0.789
Employment share at businesses with 20–49 employees	2703	0.118	0.04	0.016	0.342
Employment share at businesses with 50–249 employees	2703	0.166	0.057	0.005	0.481
Employment share at businesses with 250–499 employees	2703	0.062	0.045	0	0.432
Log population	2703	10.579	1.313	7.09	16.128
High school dropout	2703	0.132	0.06	0.012	0.485
High school graduates or some college experience	2703	10.579	1.313	7.09	16.128
Black share	2703	0.095	0.144	0	0.874
Hispanic share	2703	0.091	0.132	0	0.991
Asian share	2703	0.014	0.025	0	0.359
Other races share	2703	0.059	0.068	0.002	0.833
Immigrants share	2703	0.049	0.057	0	0.533
Young employment share	2703	0.133	0.036	0.026	0.443
Old employment share	2703	0.251	0.044	0.118	0.511

Note: Dependent variable observation counts are county-days or county-weeks depending on the variable (as described in Section 3.1), and independent variable observations are simply counties because pre-pandemic county characteristics are observed at only one point in time.

5 | EMPIRICAL RESULTS

We now turn to the empirical results. Our discussion focusses on the interactions between Covid dummy and the explanatory variables to assess whether differing initial characteristics explain post-pandemic responses. The main explanatory variable effects (i.e., the coefficients on the non-interacted variables) are unreported, but they are almost all statistically insignificant, suggesting that, at least pre-Covid, fixed effects generally account for the varying county outcomes.

Recall that 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. Coefficient estimates that are statistically significant at the 1%, 5%, or 10% levels are shaded green if the estimate suggests stronger local activity and orange for weaker activity.

5.1 | Aggregate consumer spending

We begin by examining how the pandemic initially affected consumer spending with results reported in columns (1) to (3) of Table 2. We center our discussion on the pooled-sample (all counties) results in column (1), though we also discuss the "urban" metro results and "rural" nonmetro results in columns (2) and (3) if warranted. Our industry composition results suggest that counties with higher employment shares in leisure services and manufacturing experienced greater reductions in consumer spending after the emergency declaration. Specifically, a one standard deviation increase in employment in leisure services and manufacturing are respectively associated with 0.06 and 0.08 standard deviation decreases in consumer spending, all else equal. While it is typically unusual for the leisure services sector to lead the United States into recession, it is unsurprising given the pandemic that counties with greater shares in this sector initially saw larger declines in spending at restaurants, bars, and hotels. In contrast, the finding that greater manufacturing concentrations also lead local economies into the Covid recession is consistent with historical cyclical patterns (Partridge & Rickman, 2002).

However, we do not find statistically significant effects on consumer spending in counties with larger shares of employment in agriculture and mining or in the public sector. Chetty et al. (2020) conclude that the drop in US 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 certain manufacturing subsectors, where workers often work inside in close physical proximity to one another, is greater, especially compared to the agriculture sector.

The results in columns (2) and (3) of Table 2 indicate that the leisure services and manufacturing results in column (1) are driven by larger and more precisely estimated effects in nonmetro counties. This pattern is not wholly unexpected because nonmetro counties are more concentrated in manufacturing. In addition, lower rural average wages mean that rural manufacturing tends to be more labor-intensive, so large shares of rural workforces may have been exposed to declining demand for national and global manufacturing and to global disruptions in supply chains for everything from lumber to computer chips. Similarly, the larger negative nonmetro response for leisure services may be attributable to relatively severe, negative effects of the pandemic on classic tourist towns.[13] Few metropolitan areas, with the possible expectations of Orlando and Las Vegas, are as exposed or sensitive to the ebbs and flows of tourism as rural tourist destinations are.

The self-employment share coefficient and all firm-size employment share coefficients corresponding to groups with 250 or fewer employees are negative but statistically insignificant. Because the negative-coefficient pattern

[13]According to the BEA, the 2019 US metropolitan total employment and compensation shares in manufacturing respectively equaled 6.1% and 9.2%, while their nonmetropolitan shares were 10.8% and 17.2%. These statistics demonstrate manufacturing's greater concentration in rural areas. For leisure services, rural areas have high concentrations in the (outdoor) tourism sectors. For example, the overall 2019 metropolitan compensation shares for (1) arts and spectator sports; (2) museums; (3) amusement, gambling, and recreation; (4) accommodations; (5) food & drinking places: 0.55%, 0.07%, **0.51%**, **0.78%**, and 2.87%. The analogous nonmetro compensation shares are 0.08%, 0.05%, **0.55%**, **1.13%**, and 2.84% (bolded indicates a greater nonmetro share). [The metro and nonmetropolitan employment shares for leisure services are respectively 10.0% and 9.0%, in which metro/nonmetro employment is unavailable at as detailed industry level).] Thus, metro America is considerably more concentrated in arts and museum sectors, but nonmetro areas are more concentrated in recreation and accommodation services. However, at the upper tail of the distribution, leisure services are especially important in some rural areas. For example, at the 95th percentile, using County Business Pattern data provided by the Upjohn Employment Institute, the 2019 metro leisure services employment share was 19% versus 23% in nonmetro America.

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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221,544	112,914	99,603	23,558	9441	13,891
R^2	0.523	0.634	0.443	0.465	0.486	0.489

Note: The estimated specification is shown in Equation (2). The number of observations refer to the number of dependent variable observations. Note that the X covariates are measured at their initial values and represents one set of values for each county, though they are repeated in every observation. See the text for more details. Clustered standard errors are in parentheses.

***p < 0.01; **p < 0.05; *p < 0.1.

applies in all 12 cases, with some almost statistically significant, there is weak evidence that employment concentrations in small firms are associated with greater reductions in consumer spending in the early weeks and months of the pandemic. Greater employment shares in firms with 250–499 employees is only statistically significant in the metro sample. The positive coefficient suggests that metro counties with higher employment shares in relatively large businesses did not suffer as much as very small or large (the omitted group) businesses.

Overall, a region's firm-size structure does not appear to have tangible effects on the initial severity of the area's recession, a topic we return to below. This initial evidence suggests that small-firm concentration is not linked to greater (initial) economic resilience to shocks such as a pandemic (or other disasters on a national scale). This finding contradicts evidence of the positive role that small businesses play in promoting resilience, though prior research has not examined shocks on the scale of the Covid-19 pandemic (Liang & Goetz, 2016; Tsvetkova et al., 2019).

Our results likely differ from studies on previous recessions because the Covid-19 recession is so different from the "typical" recession. It severely hurt small businesses that lacked the flexibility, knowledge, resources, or liquidity to make the necessary accommodations to continue operating in the short run. Many businesses had to completely change operations—for example, changing the inside of establishments to make social distancing feasible, offering delivery for the first time, or reducing work hours to meet decreased demand—all with short notice. Our findings suggest that despite prior evidence that small businesses increase local economic resilience, there are conditions for which this claim does not apply. In particular, in the wake of a massive economic shock, many small businesses lack the capacity to undertake the necessary changes to survive.

Next, we turn to the effects of pre-pandemic demographic characteristics, and we find that more populated counties experienced larger declines in aggregate spending during the pandemic. 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 result is consistent with the idea that people in more populous counties stayed home due to fears of exposure to the virus, leading to declines in consumption, especially the consumption of goods and services in the leisure sector. 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 is also negative but statistically insignificant, a surprising result given that greater urban density facilitates the transmission of the virus.

Rural communities, nonetheless, have their own opportunities for mass infection. Consider a local rural high school basketball game (or church), which draws a significant portion of the community into one setting, creating the perfect opportunity for infecting a large share of the population. Similarly, large parts of the local rural population may regularly pass through a relatively small handful of retail stores. In addition, media portrayals suggest that rural residents have taken fewer precautions to avoid infection, such as failing to practice social distancing and wear masks.

There is likely heterogeneity in these impacts even within nonmetro areas. For example, large rural communities were more likely to enforce shutdowns than smaller ones. In addition, because smaller rural areas have limited options when meeting local supply chain demands, the shutdown of one business can have large spillovers on other local firms that depend on that business as a customer or a supplier. Part of the resilience of larger cities is attributable to multiple supply chain options, making each individual firm less critical in supporting other local urban firms. Conversely, cities usually have more diversified economies than rural communities, who often rely on one industry (often manufacturing), which again implies that problems in one industry can wreak more economic havoc in rural areas, especially smaller ones (see Coulson et al., 2020 for an example regarding diversity's role in promoting resilience).

We now turn to the education results. One standard deviation increases in the shares of high school dropouts and high school graduates/individuals with some college experience (both relative to the college graduate share) are related to 0.23 and 0.08 standard deviation changes in consumer spending, respectively. 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 effects of "typical" recessions in that less-educated workers are much more likely to be adversely affected than higher-educated workers.

County-level consumer spending also took larger hits in metro counties with larger immigrant shares. This finding may relate to Borjas and Cassidy's (2020) finding that immigrants experienced more severe job losses during the pandemic than native workers. Thus, counties with greater immigrant shares appear to have experienced more depressed consumer spending in part due to newly unemployed immigrants, many of whom did not draw UI.

Finally, our results indicate that counties with older pre-pandemic workforces saw greater declines in consumer spending relative to counties with more prime-aged workers, especially in nonmetro areas. Older workers may have more fears about virus exposure and are less willing to leave their residences for shopping (and may also be less comfortable shopping online). Older workers in nonmetro counties who previously commuted into the city for work may be less willing to do so due to concerns about exposure, which could explain why this effect is more prominent in nonmetro counties.

5.2 | Weekly change in unemployment insurance claims

Next, we assess the pandemic's impact on county labor markets by examining changes in weekly UI claims after the national emergency declaration. Consistent with the spending results, the corresponding UI pooled-model results in column 4 of Table 2 indicate that weekly claims are more responsive in areas with larger leisure services and manufacturing sectors—that is, a one standard deviation change in leisure services and manufacturing employment shares are respectively related to rather large 0.18 and 0.11 standard deviation changes in UI claims. The larger effects for UI claims versus spending are reasonable given that unemployed leisure services or manufacturing workers typically received $600 additional weekly UI PUA benefit, which supports both household spending and can incentivize UI claims. The pandemic's effect on 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, ignoring statistical significance, the point estimate for metro counties is about fives times larger than for nonmetro counties. This finding may be explained by higher UI urban take-up rates, perhaps due 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 about three-times larger than 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 production farms that typically use small workforces that are not usually in close proximity to each other.

In addition, it may be surprising that a one standard deviation increase in metro public-sector employment generates a rather large, statistically significant −0.17 standard deviation decrease in weekly UI claims, while the pooled and nonmetro results are insignificant. This suggests that public employment (at least initially) held steady, consistent with the notion that public employment has historically been less cyclically driven.

Small businesses reportedly struggled 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 insignificant at conventional levels. One key feature of the CARES Act is that self-employed workers became eligible for UI, a major change from past UI policy. Thus, this positive response may reflect the extension of UI benefits to this previously ineligible group, which interestingly did not appear to translate into increases in consumption in counties with higher shares of self-employed workers as evidenced by the negative and insignificant effects of this variable on aggregate spending.

Counties with greater employment shares in firms with under 250 employees had fewer weekly UI claims on average. However, the negative response for the 20–49 employee firm-size group was relatively small and only statistically significant for nonmetro counties. Specifically, using the pooled sample, one standard deviation increases in the firm-size employment share for businesses with under 20 employees and for businesses with 50 to 249 employees are associated with 0.13 and 0.07 standard deviation decreases in UI claims, respectively.[14]

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

The corresponding responses for metro and nonmetro counties are also statistically significant for those two categories and of similar magnitude.

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 historically qualify for benefits. Second, the firm-size results may relate to the launch of the Paycheck Protection Program (PPP), a business loan program created by the CARES Act to help self-employed workers, sole proprietors, independent contractors, and nonprofits retain their workforce. If PPP recipient firms maintain their workforce instead of laying off workers, which would increase UI claims, a part of their loan is forgiven. This incentivizes firms to retain workers and 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.

However, small businesses reportedly struggled to obtain PPP loans because of administrative hurdles, like long wait times due to banks prioritizing their biggest and best customers and fee structures favoring loans to the largest firms (Bartik et al., 2020; O'Connell et al., 2020). Therefore, counties with large employment shares in small firms could see larger increases in UI claims. On one hand, 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 as previous studies suggest. On the other hand, the weak evidence of declines in spending in counties with higher shares of small business employment presented in Section 5.1 may indicate that these firms (and their employees) still struggled. The time-use results presented in Section 5.3 should shed light on which story dominates.

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, and the negative response is more consequential in metro counties than nonmetro counties (i.e., −0.22 vs. −0.14). Yet as discussed in Section 5.1, more populated metro counties experienced statistically insignificant declines in spending, which may be attributable to widespread Covid fears in more populated areas rather than higher unemployment, conditional on the other controls.[15]

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 a 0.20–0.23 standard deviation decline in weekly UI claims. The high school dropout coefficient, while statistically insignificant, is also negative for the pooled sample. These findings support the idea that the relative increases in consumption among less educated groups documented in Section 5.1 are unlikely attributable to increased UI benefit generosity but instead to less educated workers being disproportionately employed in “frontline” jobs and sectors deemed “essential” and remaining employed consequently (Montenovo et al., 2020).

An alternative explanation is that highly educated workers better understood the CARES Act's changes to UI and were better equipped to take advantage. Yet, as the consumer spending results show, counties with lower college-graduate shares had relatively greater spending amidst the pandemic, supporting the idea that less-educated workers' spending was especially buoyed by continued employment. If these workers do become unemployed, the UI benefit top-up leads to relatively greater household spending increases. The UI benefit top-up clearly appears to have initially altered the historical pattern of less-educated workers bearing the brunt of downturns—and how education's role in affecting resilience relates to which skill levels are deemed “essential” in the wake of the negative shock.

We find no statistically significant differential effect of the Covid-19 pandemic on weekly UI claims in counties where immigrants make up a greater share of the population, perhaps because immigrants may have been less likely to claim UI in part due to Trump Administration policies that penalize immigrants who use public welfare before applying for US citizenship (Kanno-Young, 2020).

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

Finally, using the pooled sample, we find that one standard deviation changes in the population shares of young (18–25) and older (55–65) workers are associated with 0.12 and 0.44 standard deviation decreases in UI claims on average, respectively, relative to the prime-age worker share. The response of young workers is primarily driven by metro counties, whereas metro and nonmetro counties with larger shares of older workers experienced statistically significant reductions in UI claims. Young workers, especially those employed in low-skilled jobs such as warehousing or delivery, like less educated workers, may be more likely to be employed in jobs that were deemed "essential," thereby remaining at work (Montenovo et al., 2020). In addition, they may be less attached to the labor market, meaning they are more likely to be ineligible for standard UI benefits and/or less knowledgeable about them, or less likely to apply for benefits regardless of eligibility. Older workers, on the other hand, tend to benefit from seniority and are historically less likely to be fired during economic downturns because of labor hoarding (Johnson & Butrica, 2012).[16] However, as noted in Section 5.1, an older working population is associated with greater reductions in consumer spending during the pandemic. This finding coupled with the decreased UI claims is consistent with the hypothesis that Covid fears, not employment declines, are likely driving the spending response.

5.3 | Time spent away from home and time spent at work

To better assess the competing explanations behind our prior results (or provide further evidence for the explanations when the spending and UI results were consistent), we examine two related indicators of economic activity: time-spent-away from home and time-spent-at work. Table 3 presents these regression results.

As discussed in the prior two sections, counties with larger leisure services and manufacturing shares fared worse, experiencing both relative decreases in spending and increases in UI claims. The results in Table 3 support those findings, with people in counties more heavily concentrated in these two industries spending less time away from home and at work.

Counties with larger self-employed workforces experienced *increased* time spent away from home and 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, and our findings in Section 5.2 indicate that counties with larger self-employment shares saw relative increases in UI claims, despite statistically insignificant changes in consumer spending. Yet, we would then expect corresponding *decreases* in time away from work among these workers as many draw UI benefits (and self-employed workers who work at home would be unaffected). Thus, it is unclear from our findings whether self-employment promotes the local resilience because some self-employed may have increased their intensity at work, staying at home less. Others, especially those who work from home, may have decreased their work and may have drawn UI. In any event, the self-employed results in their entirety are ambiguous, and more work is needed to identify the pandemic's effect on this subset of workers.

Having larger shares of employment at firms with 19 or fewer employees is negatively and statistically significantly related to time spent away from home and at work, whereas it was negative and statistically significantly related to UI claims. This pattern, coupled with the imprecisely estimated negative effect of the smallest firm share on spending is consistent with the hypotheses that the (1) smallest firms were often forced to close, (2) relatively fewer of their employees filed for UI, but (3) some of the smallest firms actually increased their work intensity in the initial stages of the pandemic, reducing their time at home.

Another somewhat anomalous result was that population's effect on spending was insignificant in metro counties and negative in nonmetro counties, yet it was negatively related to changes in UI claims in both types of counties. As discussed in Section 5.2, the modest spending decline could be driven by either employment declines in more populated areas or by increased Covid fears, all else equal. The UI results

[16]However, this finding is inconsistent with Bui et al. (2020), who find older workers experienced more adverse economic effects from the Covid-19 downturn.

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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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)
State and time (day or week) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,719	56,781	8954	155,605	79,442	70,675
R^2	0.965	0.968	0.952	0.952	0.968	0.932

Note: The estimated specification is shown in Equation (2). The number of observations refer to the number of dependent variable observations. Note that the X covariates are measured at their initial values and represents one set of values for each county, though they are repeated in every observation. See the text for more details. Clustered standard errors are in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

suggested that the “Covid-fear” story dominates because more populated areas saw fewer UI claims. Yet, Table 3's results indicate that residents of more populated areas spent *less* time away from home and *less* time at work, which together support both stories, with workers staying at home and away from work either out of fear of exposure or because of reduced work.

Having larger shares of less educated workers (less than a Bachelor's degree) is positively and statistically significantly associated with increases in time away from 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. These results, like the UI claims results, are less supportive of the notion that less educated workers fared better because of increased UI benefit generosity and are more supportive of the idea that they fared better because of employment in “essential” occupations that required more work hours.

We obtain similar findings for counties with young workforces—i.e., using the pooled sample, one standard deviation increases in the young adult population share are associated with 0.07 and 0.005 standard deviation *increases* in time spent away from home and at work, respectively, mostly driven by young workers in metro counties. These findings coupled with the relative declines in UI claims in counties with younger workforces (and no statistically significant spending effects) suggest that younger workers, like less educated workers, may have been more likely to be employed in "essential" jobs and therefore less likely to need UI or cut back on spending. Having a greater older worker share is also positively related to time spent at work, though this pattern appears stronger in nonmetro counties. These results support the notion that older workers were less likely to draw UI, suggesting they remained in the workforce, with their lower spending levels perhaps attributable to an unwillingness to shop online or in person or to visit bars or restaurants (many of which were shutdown).[17]

Finally, metro counties with higher immigrant shares also experienced reductions in time away from at home and decreased time at work, consistent with the notion that immigrants especially faced difficult labor market challenges from the Covid recession. These results are supported by the findings of Borjas and Cassidy (2020) and our prior finding that counties with larger immigrant shares experienced greater spending declines.

5.4 | Small business openings and small business revenue

Next, we consider the pandemic's effect on small business outcomes. While the smallest businesses were more likely to close, it is important to understand how the pandemic affected revenue of the remaining small businesses and the likelihood of new, small business start-ups. The CARES Act and the resulting PPP program were supposedly targeted towards small businesses, so further examining them is important for determining those programs' effectiveness.

The results in Table 4 show, unsurprisingly, that 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 are rather large. In contrast, manufacturing employment share is statistically unrelated to small business revenue and start-ups, perhaps because small businesses typically play a lesser role in manufacturing supply chains, and consequently, may not have felt the effects of the manufacturing sector's downturn as severely. Finally, illustrating the nuanced role of population, 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, consistent with our previously discussed, ambiguous findings of firm-size composition on regional resilience during the early stages of the pandemic. We do, however, find that both metro and nonmetro counties with greater pre-Covid self-employment shares experienced rather large increases in small business openings and small business revenue, indicating that self-employed workers may have been more likely than other workers to start (additional) businesses during the pandemic. Greater self-employment concentrations may also 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 less educated population shares, and the magnitudes of the effects 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 exposure to the virus outside of the home (that reduces their willingness start a small business or shop at one), or perhaps from the general reluctance of older individuals to start new businesses, especially during uncertain times.

[17]Older rural workers may also have been more skeptical of the severity of Covid-19 and continued working.

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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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)
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^2	0.755	0.829	0.681	0.409	0.522	0.312

Note: The estimated specification is shown in Equation (2). The number of observations refer to the number of dependent variable observations. Note that the X covariates are measured at their initial values and represents one set of values for each county, though they are repeated in every observation. See the text for more details. Clustered standard errors are in parentheses.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

A greater Black population share is significantly associated with more small business activity, which may reflect the relatively strong economies in some counties with large Black populations. Based on earlier findings that counties where immigrants make up a larger share of the population experienced weaker pandemic economies, it is unsurprising that higher immigrant population shares are related to reductions in small business revenue. Indeed, these results indicate that the US structure of documented and undocumented immigrants combined with policies generally unfriendly to immigrants adversely affected local resilience.

5.5 | Low-income employment and earnings

Table 5 shows the pandemic's effect on employment and earnings for low-income individuals. We center our discussion on low-income earnings because the low-income employment results are quite similar. Not surprisingly,

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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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 × 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)
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^2	0.583	0.776	0.464	0.676	0.832	0.565

Note: The estimated specification is shown in Equation (2). The number of observations refer to the number of dependent variable observations. Note that the X covariates are measured at their initial values and represents one set of values for each county, though they are repeated in every observation. See the text for more details. Clustered standard errors are in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

the results suggest that low-income workers were adversely affected in counties with greater employment concentrations in leisure services and manufacturing. Likewise, low-income workers suffered more in populated metro and nonmetro counties, again showing population's nuanced role in transmitting the effects of the pandemic recession (e.g., urban shutdowns could have especially affected low-income workers in the leisure services industry). While many CARES Act programs trickled below the middleclass, our findings suggest that urban workers at the lowest rung still struggled, especially those in leisure services in manufacturing. The pandemic's effects were likely worse for low-income workers with relative weak labor force attachment before the pandemic and who could not qualify for UI and the associated benefit top-up.

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 other size categories. We also find increases in low-income earnings and employment in metro counties with higher shares of self-employed workers, further supporting the idea that concentrations of self-employment promote local resilience and suggesting that they even aid 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 metro counties with older pre-pandemic workforces, consistent with our findings for the other outcome variables previously discussed.

5.6 | Heterogeneous effects

In the preceding analysis, we demonstrated that local, pre-pandemic characteristics affected severity of the Covid recession. In this section, we explore whether heterogenous effects exist along two other dimensions: initial recovery speed and political leaning.

When considering initial recovery speed, we being by defining counties as either "fast recovery" or "slow recovery." Fast recovery counties are those whose average monthly consumption in first quarter of 2021 was higher than January 2020 consumption, and we classify all other counties as slow recovery. We replicated Tables 2–5 using this delineation (as opposed to metro vs. nonmetro) and found that most coefficients on our key variables for fast recovery versus slow recovery counties were not statistically distinguishable from one another, with a few key exceptions.[18] In particular, the effects of having a relatively younger or relatively older pre-pandemic workforce on pandemic economic outcomes were often significantly different in fast versus slow recovery counties. Nonetheless, whether county experienced a fast or slow initial recovery does not appear to majorly influence the extent to which pre-pandemic local characteristics affected the severity of the recession.

Second, to explore if a county's political leaning was another determinant of economic activity in the early stages of the pandemic, we added an interaction between our Covid dummy and the county vote share for Donald Trump in the 2016 Presidential election. President Trump's statements and policies may have produced different behaviors among some groups in some counties, which may underlie the prior results. Indeed, his election support was strongest in rural or outer exurban parts of metro areas, and his support was quite strong among less-educated whites (Goetz et al., 2018). Likewise, areas with the heaviest support for Trump also were the ones whose residents appear to share his oft-stated skepticism regarding the severity of Covid-19. If they view Covid-19 as an inconvenience rather than a major threat, such regions may have maintained "business as usual," reducing the severity of the initial recession impact.

The coefficients on the "Trump share" interaction for all eight dependent variables are presented in Table 6. Generally, our other variable results remained quite similar, so we focus on the Trump interaction term. All are coefficients positive, which suggests that across almost all outcomes, economic activity was higher in the early stages of the pandemic in places that supported Donald Trump, no matter whether the counties are rural or urban. However, the positive coefficients for the UI claims dependent variable suggests that counties with larger Trump vote shares, in addition to experiencing larger spending increases, more time away from home or more time at work, greater small business openings and revenue, and higher low-income earnings and employment, also saw larger

[18]We do not present these results for brevity but they are available from the authors upon request.

TABLE 6 Pandemic economic activity in counties with larger 2016 Trump vote shares

Dependent variable	Total	Metro	Nonmetro
Aggregate spending	0.330**	0.363**	0.373
	(0.153)	(0.180)	(0.263)
Increase in weekly UI claims	2.506***	3.625***	1.663***
	(0.393)	(0.752)	(0.361)
Time spent away from home	0.550***	0.473***	1.565***
	(0.0985)	(0.101)	(0.223)
Time spent at workplace	0.152***	0.128***	0.181***
	(0.00984)	(0.0127)	(0.0142)
Small business openings	1.740***	1.521***	1.951***
	(0.126)	(0.153)	(0.204)
Small business revenue	0.626***	0.712***	0.482*
	(0.150)	(0.199)	(0.252)
Low-income earnings	0.540***	0.370**	0.690***
	(0.139)	(0.146)	(0.242)
Low-income employment	0.615***	0.442***	0.777***
	(0.127)	(0.137)	(0.221)

Note: See the notes to Tables 2–5 and the text for further details. Clustered standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

increases in weekly UI claims. This could be due to more knowledge of the CARES Act in pro-Trump counties given President Trump's supported of it. While more research is necessary to identify the mechanisms, the findings in Table 6 suggest that strong support for President Trump appeared to dampen the initial impact of the Covid recession.

6 | CONCLUSION

The Covid-19 pandemic is a unique opportunity to assess a geographically widespread natural disaster that closed much of the national economy. Most work on regional resilience examines shocks such as natural disasters with more localized effects. Prior resilience research about recovery from recessions also does not typically consider global supply chain disruptions or severe workforce disruptions due to fears of exposure to a virus or immediate changes in household obligations, like childcare. This study's first contribution is to assess differences in how the immediate and widespread Covid recession was transmitted across local economies. Second, to better understand the regional characteristics that affect local resilience, we identified the pre-pandemic county characteristics that produced spatial economic patterns that so differed from previous recessions.

Using weekly county-level data, we examined the pandemic's effects on local aggregate consumer spending, UI claims, time-at-home and time-at-work, small business openings and revenue, and low-income employment and earnings. Our key findings indicate that the Covid recession's impacts varied from the impacts of prior economic downturns. For example, while local concentrations of manufacturing negatively impacted counties in the more typical manner, the adverse role played by higher concentrations of leisure services was even larger in the Covid recession. While the apparent negative impact of leisure services on resilience is likely unique to this recession, higher local concentrations of manufacturing employment is consistently a negative factor in this and past research. Manufacturing seems to harm local resilience because its initial negative response is disproportionately larger than for other sectors, while its slow-growth nature does little to support long-term growth. This recession further shows how supply chain breakdowns further inhibit portions of manufacturing.

More populated metro and nonmetro counties generally experienced greater economic hardship, meaning agglomeration economies generally did not shield populated areas from adverse economic effects, though the population effects were nuanced. Furthermore, according to the regional resilience literature, small businesses should play a positive role in mitigating the effects of an economic downturn, but the effects of the local firm-size structure are ambiguous in this case. In particular, a greater employment concentration in small firms is associated with fewer UI claims, but we find no other economic effects of firm-size structure except for on reductions in time spent at work—suggesting that relatively fewer UI claims may have had more to do with fewer small business employees qualifying for or knowledgeable about UI.

Interestingly, counties with younger workforces experienced fewer UI claims and *increases* time spent at work. It is unclear whether this pattern is due to young workers supplying labor for highly demanded services such as delivery or attributable to young workers disproportionately remaining in the workforce due to lesser concerns about exposure to the virus. Similarly, counties with larger shares of less educated residents saw relative increases in time at work, fewer UI claims, higher aggregate spending, better small business performance, and higher incomes for the lowest earners. Therefore, compared to past recessions, the expected age and education effects were reversed, with younger and less educated workforces associated with more favorable economic outcomes in the early stages of the Covid recession. A clear takeaway from our research is that extrapolating from past recessions can produce misleading predictions when assessing recessions of unique origins. Likewise, making general claims about the extent to which local factors impact resilience is not possible because this depends on the set of skills that are demanded during the downturn, which in turn, depends on the type of negative shock.

Our results also point to a wide array of future research paths. For example, the "nontraditional" demographic and industry findings indicate an urgent need to appraise how the $600/$300 UI top-offs and PPP affected behavior (or when they did *not* affect behavior). This study needs to assess both labor market outcomes and spending behavior. Likewise, it is crucial to understand when and where supply chain disruptions are most damaging, which will be critical for understanding how industry composition affects local resilience to widespread disasters. Moreover, because the origin of the negative shock appears to impact which local characteristics foster resilience, a broader assessment of the tradeoffs is warranted when governments promote factors typically associated with greater resilience (say, education or small business employment) but can produce ambiguous or adverse effects in response to other (rarer) shocks.

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CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

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