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COVID-19, the New Urban Crisis, and Cities: How COVID-19 Compounds the Influence of Economic Segregation and Inequality on Metropolitan Economic Performance

Richard Florida[1] and Todd Gabe[2]

Abstract

This paper examines the connection between measures of a U.S. metropolitan area's new urban crisis (i.e., unaffordable housing, economic inequality, and residential segregation) and its year-over-year employment change in the period immediately before and during the COVID-19 pandemic. Results show that measures of the new urban crisis did not generally have a statistically significant association with year-over-year employment change between January and September of 2020, which captures the period before COVID-19 and the beginning of the pandemic (e.g., shutdown). The severity of a region's economic segregation and inequality, however, are associated with higher rates of employment decline in the early recovery months of October to December of 2020. These findings suggest that places that rate worse for indicators of the new urban crisis were less able to recover from the negative economic shocks related to COVID-19.

Keywords

urban crisis, economic inequality, economic segregation, workforce development, economic development

Many large cities in the United States and worldwide are experiencing a new urban crisis (Florida, 2017). This crisis is characterized by a deepening residential segregation of households, increasing economic inequality, and rising housing costs that are unaffordable to many low- and medium-income households. This new urban crisis differs from the original urban crisis of the 1970s and 1980s in that, while the earlier period was marked by urban decline, deindustrialization, and a flight of capital and talent, the current crisis is one of urban success. Although economic vibrancy is not necessarily a direct cause of regional inequality, many of the adverse economic conditions that describe the new urban crisis are fueled by the productivity and economic success of cities. That is, many of the places that rate among the nation's leaders in terms of the innovation economy and human-capital-driven growth are also suffering the greatest impacts of the new urban crisis.[1] As the impacts of the COVID-19 pandemic have spurred a shift away from superstar cities and tech hubs, it has led to a surge of housing demand and prices in suburbs, second- and third-tier cities, and rural areas, causing the new urban crisis to become a more general crisis of places across America.

In early 2020, virtually all regions of the world were impacted by the very large and sudden health and economic crisis of the COVID-19 pandemic. The number of U.S. cases grew rapidly from fewer than 100 cases on March 1, 2020, to over 1 million cases on May 1, 2020.[2] One year later, by May 2021, the United States had over 30 million cases of COVID-19. During the rapid spread of COVID-19 in the spring of 2020, year-over-year U.S. private nonfarm employment fell by 15.2% in April.[3] After the steep employment drop in April, the year-over-year decreases became progressively smaller from May (12.8% decline) to December (6.2% decline) of 2020. The economic impacts of COVID-19 were much larger on low-wage workers than people who earn higher wages. For example, data from the Opportunity Insights project show that employment rates of high-wage workers returned to the pre-pandemic benchmark by late May 2020, whereas the employment rates of low-wage workers were 20% below the pre-pandemic benchmark in the middle of September 2020 (Chetty et al., 2020). Likewise—and, in part, driven by the heterogeneity of impacts across different types of workers—the economic impacts associated with the COVID-19 pandemic differed

[1]Rotman School of Management, University of Toronto, Toronto, Canada
[2]School of Economics, University of Maine, Orono, ME, USA

Corresponding Author:
Todd Gabe, School of Economics, University of Maine, 5782 Winslow Hall, Orono, ME 04469, USA.
Email: todd.gabe@maine.edu

substantially across regions. Year-over-year employment change in April 2020 fell by 27% in Las Vegas, compared with an 8% decline in Salt Lake City. In December 2020, year-over-year employment increased in a few U.S. metropolitan areas such as Provo, Utah, compared with a more than 15% decrease in Honolulu, and Midland, Texas.

Understanding the wide heterogeneity in the employment growth rates across places, especially at the end of 2020 when some regions were starting to recover from the COVID-19 economic shock, provides some indication of the (economic) resilience of U.S. regions. According to USAID, resilience is defined as "the ability of people, households, communities, countries, and systems to mitigate, adapt to, and recover from shocks and stresses in a manner that reduces chronic vulnerability and facilitates inclusive growth" (Shah, 2012).[4] Although the regional economic declines experienced during the COVID-19 shutdown and very early months of the pandemic are likely a reflection of a place's industry and occupational structures, as well as the severity of the COVID-19 outbreak and measures to counter it, the economic performance of regions by the end of 2020 might provide some indication of their ability—at least in terms of employment growth—to "adapt to" and "recover from shocks." In other words, the areas with higher rates of economic growth (or lower rates of decline) in the latter months of 2020 can be thought of as more resilient (in terms of employment growth).[5]

Previous studies have investigated aspects of regional economic resilience such as patterns of regional employment and wages following large shocks (Blanchard et al., 1992; Feyrer et al., 2007). Kolko and Neumark (2010) considered the role of business ownership and show that the presence of corporate headquarters helps "insulate" regions from negative economic shocks. Chapple and Lester (2010) examined two types of resilience—a "new equilibrium" and "reversing path dependency"—and found that the keys to regional transformation include building a high-tech economy, retaining manufacturing, and attracting immigrants. Past research has also focused on the resilience of regions in their recovery from the Great Recession (Brakman et al., 2015; Ezcurra & Rios 2019; Han & Goetz, 2015; Mazzola et al., 2018; Ringwood et al., 2019). These studies looked at the effects of urbanization, industry structure, human capital, and governance on the resilience of regions to the large economic shock of the 2008 worldwide recession. Although we consider similar characteristics in our analysis of the employment change of U.S. metropolitan areas during the early recovery from the COVID-19 economic shock, we focus on the connection between the resilience of regions and aspects of the new urban crisis such as the residential segregation of households (e.g., by income and occupation), housing unaffordability, and measures of economic inequality.

Specifically, this research examines the relationship between year-over-year monthly employment change in U.S. metropolitan areas over the course of 2020 and indicators of the new urban crisis. We focus on employment change as the outcome of interest because employment numbers capture the intersection of the demand for workers by businesses and the supply of workers by people in the labor force. Both factors might have been affected by the COVID-19 pandemic. Given that, in some places, the last few months of 2020 marked the beginning of a region's recovery from the COVID-19 economic shock, the analysis shows how elements of economic segregation and inequality are associated with employment change and (to some extent) the resilience of regions following a large health crisis. Although our findings might be suggestive of how aspects of the new urban crisis impacted regions immediately prior to and during the COVID-19 pandemic, our results do not show "causal effects." Results presented in the paper do not generally uncover statistically significant relationships between year-over-year employment change in the early months of 2020 and our measures of the new urban crisis. The severity of a region's economic segregation and inequality, however, are associated with higher rates of employment decline in the early recovery months at the end of 2020.

New Urban Crisis

The new urban crisis is described as a combination of unaffordable housing prices, high wage and income inequality, and vast levels of residential segregation along a variety of dimensions (Florida, 2017). In essence, the new urban crisis is a deepening of the segregation, inequalities, and disadvantage found in many U.S. and worldwide metropolitan areas. On the one hand, cities are hotbeds of innovation and creativity, and big cities tend to be our most productive regions (Glaeser, 2011). On the other hand, the high wages and incomes generated through innovation and earned by knowledge and creative workers, along with a growing demand for lower-paid service workers in many urban areas, is contributing to wide income and wage disparities, unaffordable housing in some neighborhoods, and gentrification.

To capture patterns of economic segregation and inequality across regions, we consider a composite index—using values taken directly from Florida's (2017) book—that measure aspects of the new urban crisis. Specifically, the *New Urban Crisis Index* is constructed using data on housing unaffordability, wage and income inequality, and the residential segregation of households by educational attainment, income, poverty, and occupational group (e.g., creative workers). Some of the places with the least favorable conditions according to the *New Urban Crisis Index* are Bridgeport-Stamford-Norwalk, Los Angeles, New York, San Francisco, and Miami (Florida, 2017). At the other end of the spectrum, metropolitan areas such as St. George, Utah; Glens Falls, New York; Casper, Wyoming; and Sheboygan, Wisconsin, rate better according to this index.

In an extension to the main analysis, we consider individual metropolitan area characteristics that are combined to form the *New Urban Crisis Index*. The specific indicators of urban distress that we use are: (1) the Gini coefficient of income inequality, (2) a measure of housing unaffordability related to the cost of owner-occupied housing relative to income, (3) residential segregation by income, (4) residential segregation by educational attainment, and (5) residential segregation by broad occupational group. The Gini coefficient, which is an indicator of income inequality within a metropolitan area, is from the 5-year sample of the 2019 American Community Survey. The Gini coefficient ranges from 0.39 to 0.54 in our sample of 347 U.S. metropolitan areas, where larger values indicate higher levels of income inequality. Some of the U.S. metros with the highest income inequality include New York, Miami, and New Orleans—as well as smaller regions such as Naples, Florida, and Valdosta, Georgia—whereas Hinesville, Georgia; Fairbanks, Alaska; and Jefferson City, Missouri, are among the places with the lowest levels of income inequality.

As a measure of housing unaffordability, we use data from the 5-year sample of the 2019 American Community Survey on the median monthly costs of owner-occupied housing (for housing units with a mortgage) multiplied by 12, and this amount is divided by median household income. This is an estimate of the percentage of income spent on housing. The U.S. metropolitan areas with the highest levels of housing unaffordability by this measure include Los Angeles, Honolulu, and San Luis Obispo, California, whereas Kokomo, Indiana; Columbus, Indiana; and Fort Wayne, Indiana, are among the regions with the lowest costs of owner-occupied housing relative to incomes.

To measure residential segregation within metropolitan areas, we examine the extent to which households and individuals (by selected economic characteristics) are concentrated within census tracts of a metro versus more evenly spread out across the entire region.[6] The measure of residential segregation by income considers families that are below the poverty line and, as a separate measure and capturing the other end of the income spectrum, households with annual incomes of $200,000 or more.[7] For example, we use Equation 1 to calculate the residential segregation of high-income (i.e., $200,000 or more per year) households within a metropolitan area:

$$0.5 \sum_{i=1}^{N} \left| \left(\frac{xi}{X}\right) - \left(\frac{yi}{Y}\right) \right| \tag{1}$$

where i indexes the census tracts within a metropolitan area (with a total of N tracts in the region), x_i and X represent the number of high-income households in census tract i and the entire metropolitan area, and y_i and Y represent the number of non-high-income households (i.e., less than $200,000 per year) in the census tract and metro. This measure can range from zero to one, where larger values indicate higher levels of residential segregation. We use a similar approach to measure the residential segregation of families that are in poverty, and we take the average of the two segregation values to arrive at a measure of residential segregation by income (Florida, 2017). Some of the metropolitan areas with the highest residential segregation by income include Detroit, Memphis, and Kansas City, whereas St. George, Utah; Fond du Lac, Wisconsin; and Williamsport, Pennsylvania, are among the places with the least concentrated patterns of residential location by income.

We use the same general approach to measure the residential segregation of people by educational attainment and occupational category. For educational attainment, we focus on individuals aged 25 and older who have a 4-year college degree or more formal education and, in a separate analysis, those without a high school diploma. Using Equation 1 to measure the residential segregation of people with a 4-year college degree, x_i and X represent the number of people (aged 25 and older) with at least a 4-year college degree in census tract i and the entire metropolitan area, and y_i and Y represent the number of people without a 4-year degree in census tract i and the entire region. Similar calculations are performed to measure the residential segregation of people (aged 25 and older) without a high school diploma, and we use the average of these two indicators as the measure of residential segregation by educational attainment (Florida, 2017).

For occupational category, we focus on employed individuals aged 16 and older and use Florida's (2002) classifications of the Creative, Service, and Working Classes. Using Equation 1 to measure the segregation of members of the Creative Class, x_i and X represent the number of workers aged 16 and older in creative occupations (e.g., artists, engineers, scientists, educators, lawyers, physicians, financial analysts) in census tract i and the entire metro, and y_i and Y are the number of workers outside the Creative Class in census tract i and the metropolitan area. We use this measure along with similar indicators of the residential segregation of members of the Service (e.g., retail sales and food service occupations) and Working (e.g., construction and production occupations) Classes to measure residential segregation by broad occupational group (Florida, 2017). The metros with the highest levels of residential segregation by occupation include San Jose, New York, and Seattle, whereas Dover, Delaware; Rocky Mount, North Carolina; and Fargo, North Dakota, are among the regions with the lowest residential segregation by occupation.

These five metropolitan area indicators measure individual aspects of the new urban crisis facing many large regions of the United States and worldwide. To examine the extent to which these variables as a group are connected to Florida's (2017) *New Urban Crisis Index* constructed using data from earlier years (e.g., 2010), we calculated an average value of the five indicators after standardizing the variables (i.e., Z-scores) into the number of standard deviations that a metropolitan area lies above or below the mean. The average *Z*-score across the five indicators has a high correlation ($r = 0.87$) with the values of the *New Urban Crisis Index* reported by Florida (2017).

Economic Impacts of COVID-19

Along with its very large and serious impacts on health and overall well-being, the COVID-19 pandemic led to very large declines in economic activity. For example, U.S. private nonfarm employment fell by 15% between March and April of 2020, and the U.S. unemployment rate increased from 4.4% to 14.8% over these two months at the beginning of the pandemic.[8] The economic impacts of COVID-19, however, varied widely across industries, occupations, and places (Gabe & Florida, 2021). Some of the hardest hit sectors were Amusement, Gambling, and Recreation (56.8% decline from April 2019 to 2020) and Food Services and Drinking Places (48.2% decline), whereas industries such as Computer and Peripheral Equipment Manufacturing (6.3% increase) and Waste Management and Remediation Services (0.2% increase) performed better.

Extensive research by Chetty et al. (2020; i.e., Opportunity Insights team) examined the impacts of COVID-19 on a variety of national and regional indicators. For example, they uncovered a 30% reduction in the daily spending of high-income households between February (pre-pandemic) and the end of March 2020, compared with a 20% decrease in the spending of low-income households. In addition, Chetty et al. found that about two-thirds of the reduced spending came from transactions that require in-person contact. On the other hand, spending on luxuries such as home pools and landscaping services increased after the start of the COVID-19 pandemic. Just as there were differences in the impacts of COVID-19 on various types of households and goods, Chetty et al. uncovered substantial heterogeneity in the impacts of COVID-19 across regions of the United States.

The COVID-19 economic crisis led to a new way of describing occupations and sectors of the economy. When analyzing the economic impacts of the pandemic, occupations and industries were characterized by the extent to which they are amenable to remote work or telework, perform essential duties, require close physical proximity, and are, generally, at risk relative to COVID-19 (Avdiu & Nayyar, 2020; Barbieri et al., 2022; Dingel & Neiman, 2020; Forsythe et al., 2020; Kane & Tomer, 2021). Focusing on jobs that are "teleworkable," Mongey et al. (2021) found that people in jobs that cannot be done from home are less apt to be White, have a college degree, own their homes, or have employer-provided health care. These characteristics of at-risk workers have features that are like those most adversely impacted by the new urban crisis. The new urban crisis is fueled, in part, by the high productivity and wages of workers in creative and high human capital jobs, compared with those in service occupations. As noted above, many of the economy's highest paying jobs were among the positions that were least impacted by the COVID-19 pandemic.[9] This means that on top of the inequalities present in many regions prior to COVID-19, the pandemic added an extra burden to low-income workers who are more likely to be in at-risk jobs.

Studies have examined the economic impacts of COVID-19 on individual workers, businesses, and regions small (e.g., counties) and large (e.g., nations; Bartik et al., 2020; Couch et al., 2020; Han et al., 2020; Walmsley et al., 2021). Much of the research on individual workers uses microdata from sources such as the monthly Current Population Survey to analyze the effects of COVID-19 on employment status (Cho et al., 2021; Couch et al., 2020; Lee et al., 2021; Montenovo et al., 2020). These studies generally found disparities in the impacts of COVID-19 related to socioeconomic characteristics such as race, gender, age, and education. Cho et al. (2021) also considered the influence of regional characteristics and found larger negative impacts on individual employment status in metropolitan areas with more than 5 million people, and that differences across metropolitan areas are related to the COVID-19 infection rate as well as industry structure and employment density. Mueller et al. (2021) focused on the self-reported economic well-being of U.S. rural residents and found that over 50% of the survey respondents felt that the health of their local economy was "poor" during the pandemic, but close to one-half believed that the local economy would be "good" 1 year in the future.

Regional research also identified large economic impacts of COVID-19 on U.S. areas and places worldwide. For example, Yilmazkuday (2021) analyzed the effects of COVID-19 on economic welfare across U.S. counties. This study considered the trade-offs between household consumption and COVID-19 cases, where both are connected to the mobility behavior of people. Results show an 11% average reduction in welfare between February and December of 2020, with wide heterogeneity across counties. For instance, some of the hardest hit counties had welfare losses as high as 46% on average over the entire period, with daily welfare reductions of 97% at the end of March. Likewise, Fana et al. (2020) examined the impacts of COVID-19 on employment in Germany, Spain, and Italy, and found that the effects varied widely both across and within countries.

This research builds from previous studies on the economic impacts of COVID-19 and contributes to this budding literature in several ways. Previous studies on the economic impacts of COVID-19 focused on the employment status (e.g., unemployed, out of the workforce) of individual workers (Cho et al., 2021; Couch et al., 2020; Lee et al., 2021; Montenovo et al., 2020). Our research, on the other hand, examines the percentage change in employment measured at the regional level. Like other studies, however, our analysis controls for characteristics such as the physical proximity of workers (Barbieri et al., 2022; Gabe & Florida, 2021), the ability to work from home (Dingel & Neiman

2020; Glaeser et al., 2022; Sostero et al., 2020), the importance of essential industries (Kane & Tomer, 2021), and the influence of population density (Hamidi et al., 2020).

In addition, complementing previous research about the resilience of regions relative to large economic downturns (Brakman et al., 2015; Ezcurra & Rios, 2019; Han & Goetz, 2015; Mazzola et al., 2018; Ringwood et al., 2019), we focus on how elements of the new urban crisis are associated with year-over-year employment change in the months before and after the COVID-19 economic shock. Although employment change following the shock gives a narrow view of regional resilience, it does provide evidence related to a region's short-term employment recovery following the COVID-19 shutdown. Whereas others have looked at differences in a region's resilience to the Great Recession of 2008, including Geelhoedt et al. (2021) who considered how regional inequalities affect resilience, our paper is one of the first to connect measures of regional inequality to the resilience of regions relative to the COVID-19 economic shock. Past research on regional resilience during and after the Great Recession of 2008 is informative about the characteristics that might impact a region's recovery from the COVID-19 economic shock, but the two events are quite different. The COVID-19 economic shock was unique in its almost total shutdown of economic activity at the beginning of the pandemic, and related measures that limited transportation and mobility around cities. In addition, the COVID-19 pandemic encouraged some residents (e.g., higher income) to leave cities and work remotely from less-dense regions and places with lower levels of COVID-19 cases.

Monthly U.S. Metropolitan Area Employment Change in 2020

We examine year-over-year employment change in all twelve months of 2020 across 347 U.S. metropolitan areas. This covers three months (January, February, and March) before the impacts of COVID-19 surfaced on U.S. employment conditions (i.e., pre-pandemic), the period of April to August that is characterized by the COVID-19 shutdown and early months of the pandemic, and the balance of the year (September to December) when some regions loosened their COVID-related restrictions and began to recover from the economic impacts of the pandemic.

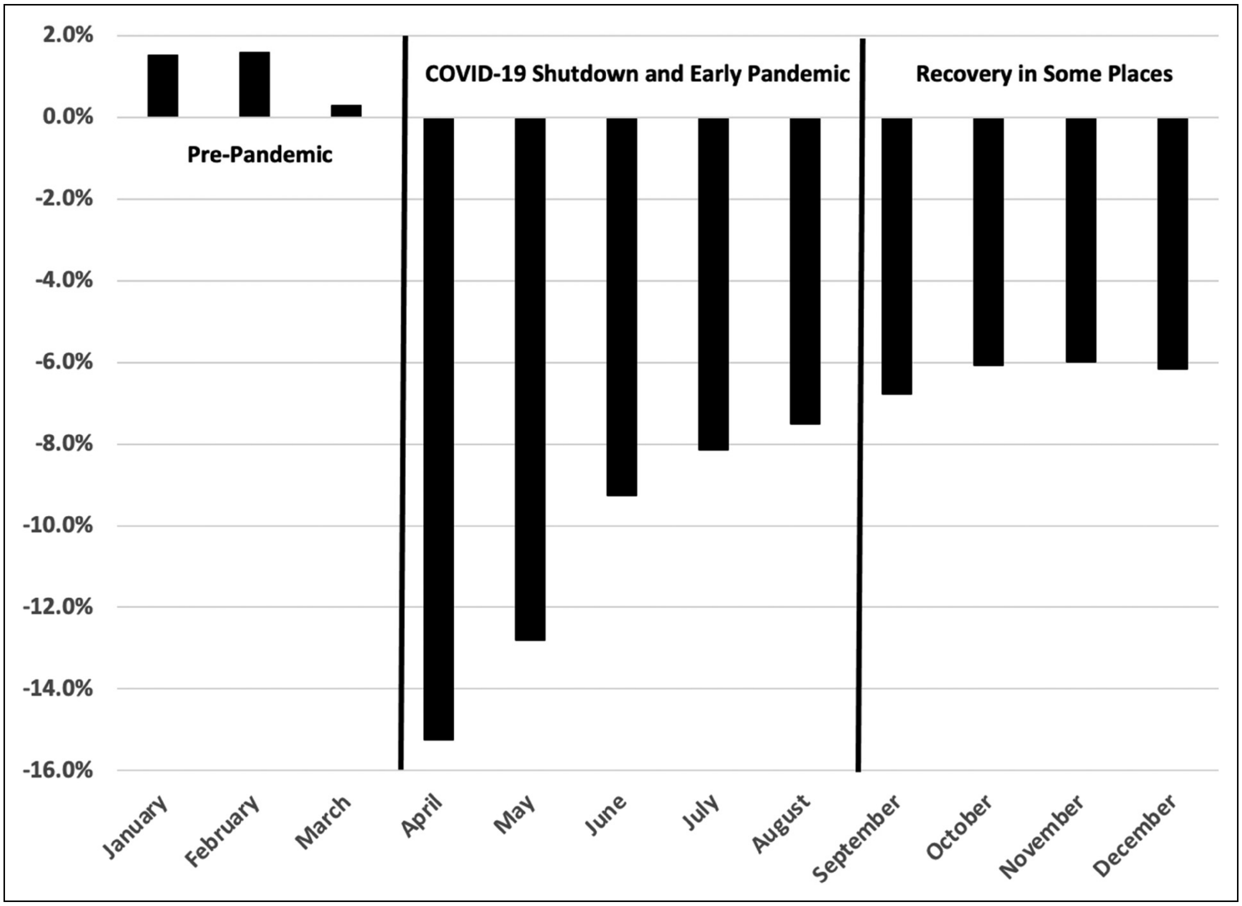

Figure 1. Year-over-year growth rate of U.S. private nonfarm employment: January to December 2020.

Figure 1 shows year-over-year rates of change for private nonfarm U.S. employment in the months of January to December of 2020. In the three months prior to the pandemic, the U.S. economy saw modest increases in private nonfarm employment. Employment fell by 15.2% between April 2019 and 2020, which was the "first" month of the pandemic, and year-over-year employment declines exceeded 8% in four of the five shutdown and early pandemic months. Over the final four months of 2020, as some regions started to recover from the COVID-19 economic shock, year-over-year employment declines ranged from 6% to 7%.

Figures 2 to 4 show the distribution of year-over-year metropolitan area employment change in the months of January (pre-pandemic), April (COVID-19 shutdown), and December (early recovery in some places) of 2020.[10] In January, the median 12-month employment growth rate was a 0.9% increase across the 347 U.S. metropolitan areas, and 87 had growth rates that exceeded 2%. Only 12 metropolitan areas had employment declines of more than 2% between January of 2019 and 2020. The relative economic performance of U.S. metropolitan areas between January 2019 and 2020 was largely similar to the employment growth experienced in previous years. For example, there's a 0.50 correlation between the employment growth rate from January 2019 to 2020 and the longer-term growth from January 2011 to 2019. This high correlation between the 2019 to 2020 growth rate and past growth is similar to the patterns found in February ($r = 0.50$) and March ($r = 0.47$). Simply put, the relative economic performance of U.S. metropolitan areas was reasonably stable and persistent in the pre-pandemic period of January to March of 2020.

In April of 2020, the median rate of 12-month employment change was −14.7%, and almost one-fifth of the 347 U.S. metropolitan areas saw employment losses of more than 20%. Although all metros experienced a reduction in employment between April 2019 and 2020, Figure 3 shows that the COVID-19 economic shocks differed considerably across regions. For example, 35 out of 347 metros had employment decreases of less than 10%, compared with 14 that saw employment reductions of more than 25%. Whereas the relative performance of U.S. metropolitan areas was largely stable in the months leading up to COVID-19, the economic shock felt at the beginning of the

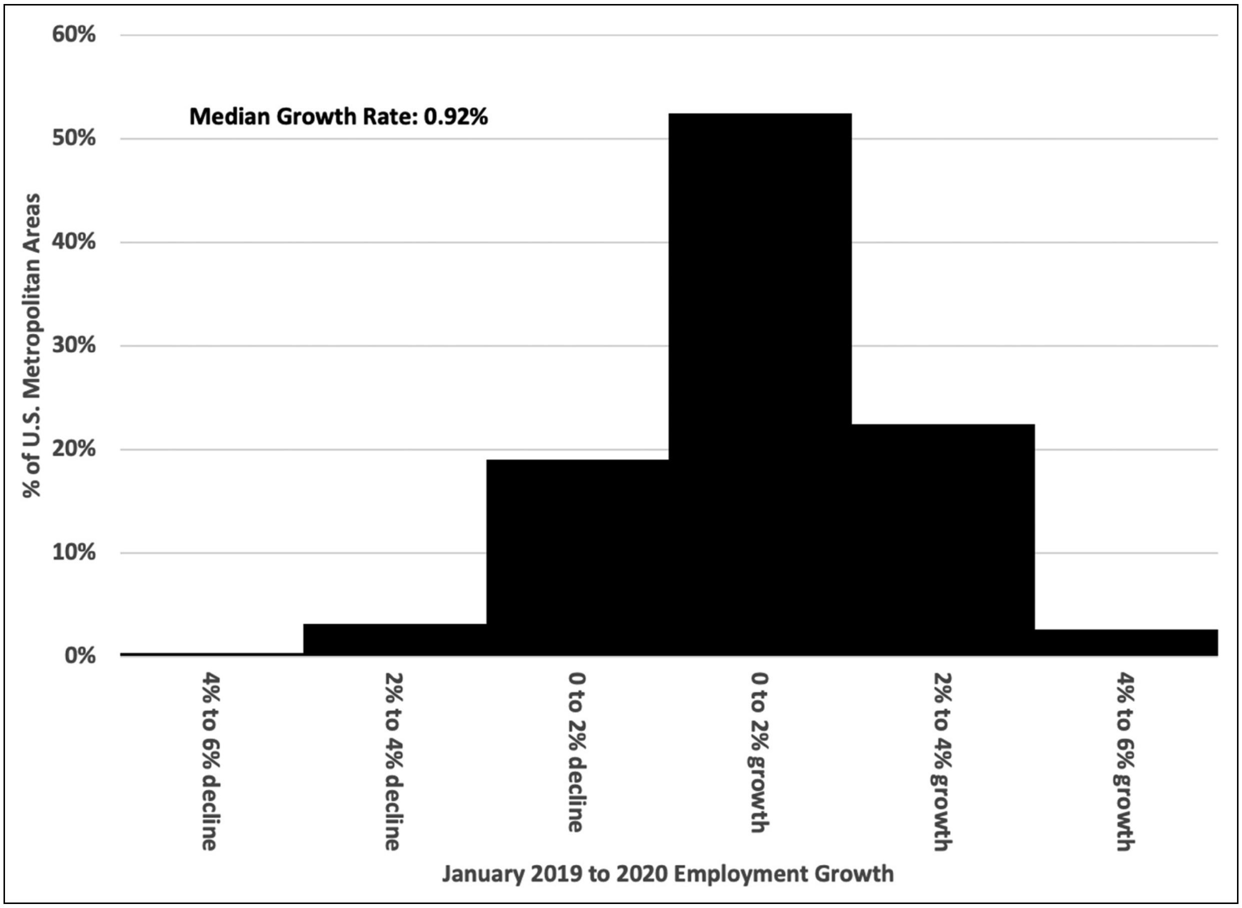

Figure 2. Distribution of U.S. metropolitan area private nonfarm employment growth ($n = 347$): January 2019 to 2020.

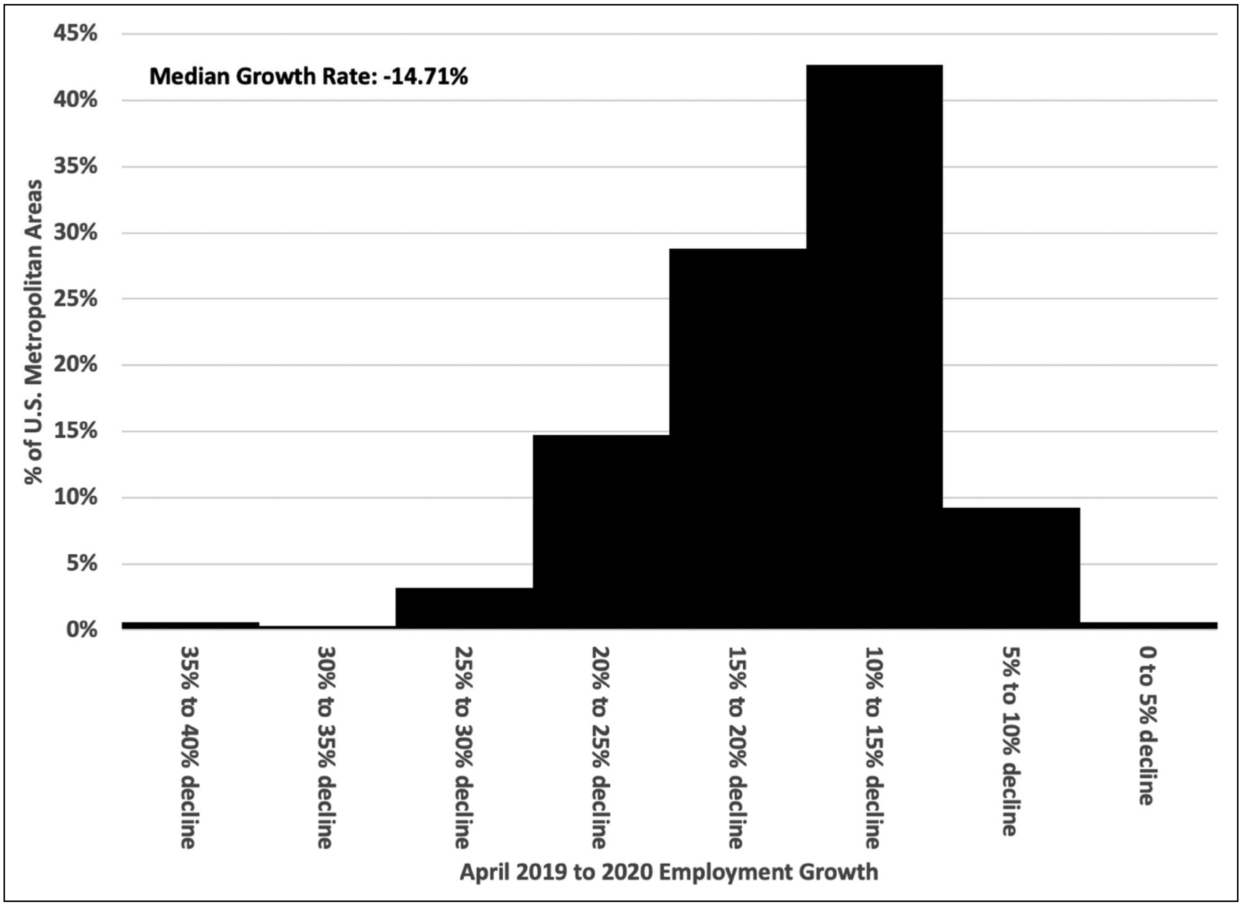

Figure 3. Distribution of U.S. metropolitan area private nonfarm employment growth ($n = 347$): April 2019 to 2020.

pandemic bore little resemblance to past rates of employment growth. For example, there's a relatively low correlation ($r =$ 0.17) between a U.S. metro's year-over-year employment change from April 2019 to 2020 and the growth rate of employment between April of 2011 and 2019, compared with the much higher correlation in January ($r = 0.50$). Furthermore, the correlation ($r = 0.40$) between a metro's year-over-year employment change in April and January of 2020 is much lower than the correlation ($r = 0.94$) between year-over-year employment change in January and February of 2020 (prior to COVID-19).

This means that the COVID-19 economic shock led to an almost total reshuffling of the deck of the employment growth experienced by U.S. metropolitan areas. For example, the Flagstaff, Arizona, metropolitan area had the 21st largest employment shock (i.e., employment decline from April 2019 to 2020) associated with COVID-19, despite being the 10th ranked metropolitan area for employment growth between January 2019 and 2020. On the other hand, the Lewiston, Idaho, metropolitan area experienced a relatively small COVID-19 employment decline of 7.4%, after being the 166th slowest growing metropolitan area between January 2019 and 2020.

Figure 4 shows a wide variation in metropolitan area year-over-year growth rates in December 2020, a month in which some regions were recovering from the COVID-19 economic shock. U.S. metropolitan areas had a median employment growth rate of −5.7%, and 40 out of 347 metropolitan areas had employment fall by more than 10%. At the other end of the spectrum, 10 metropolitan areas experienced employment growth between December 2019 and 2020. The relative economic performance of U.S. metropolitan areas during the early recovery months of September to December had a low correlation with performance prior to the pandemic. The correlation between year-over-year employment growth rates in September, October, November, and December of 2020, with growth rates calculated using data between 2011 and 2019, are 0.10, 0.10, 0.11 and 0.13, respectively.

The large change in the relative performance of U.S. metropolitan areas suggests that the factors that impact the growth of regions will differ in the three months leading up to the pandemic, during the shutdown and early pandemic period, and in the months of September to December as some places started their recovery from the COVID-19 economic shock. The regional characteristics that increase the

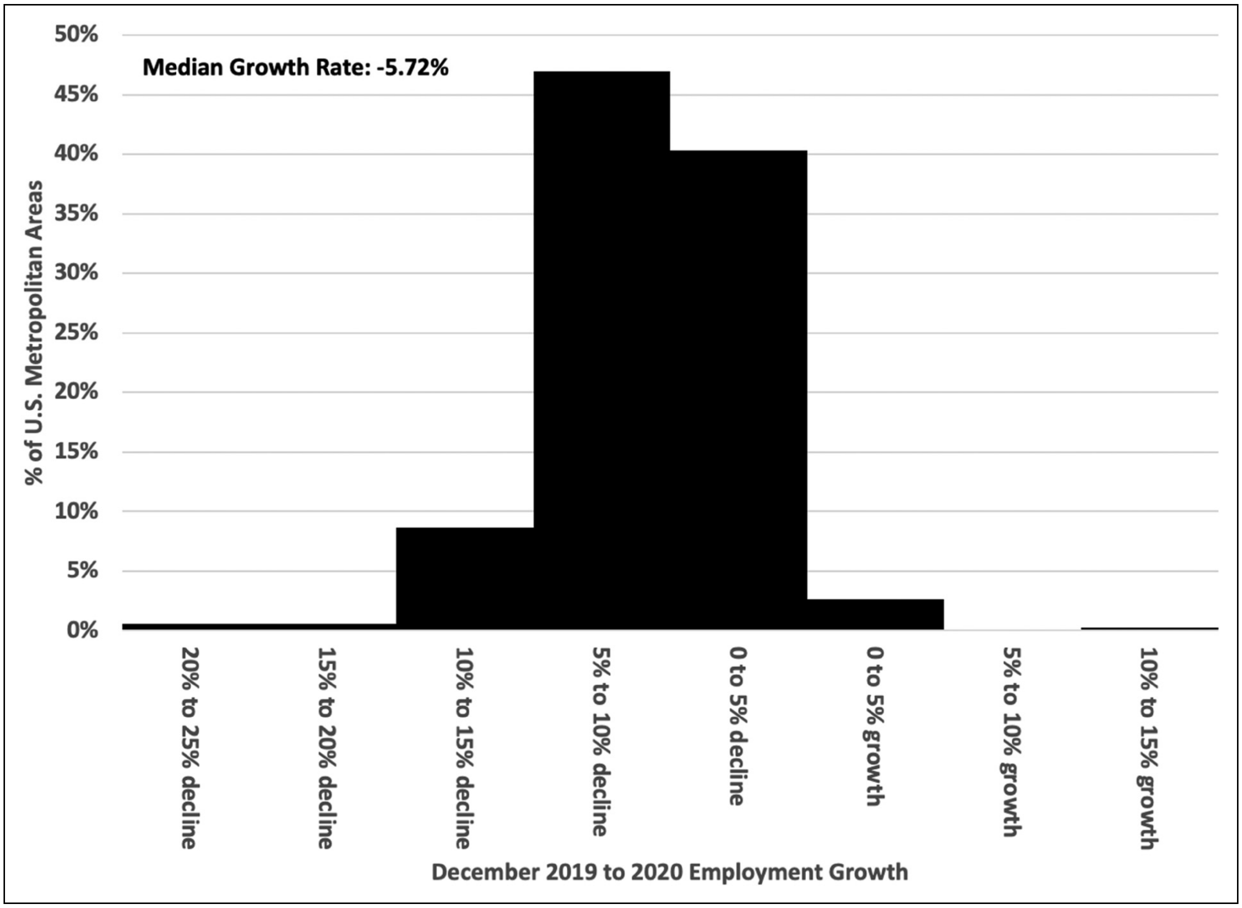

Figure 4. Distribution of U.S. metropolitan area private nonfarm employment growth ($n = 347$): December 2019 to 2020.

growth of regions between January and March reflect the factors that support growth during an expansionary period, as the United States had employment growth rates of 1.5%, 1.6%, and 0.3% in these three months. The factors that influence the year-over-year employment change over the months of April to August show the regional characteristics that impacted the magnitude of the COVID-19 economic shock during the shutdown and early pandemic period. Finally, the factors that influence the employment change that occurred between September 2020 and December 2020 are a mix of the characteristics related to the impact of the pandemic itself, but also the ability of regions to recover from the COVID-19 economic shock.

Conceptual Foundation

The empirical analysis involves estimating the following regression model using data for 347 U.S. metropolitan areas:

Year-Over-Year Employment Change $= \beta_0 + \beta_1$ *New Urban Crisis* $+ \beta_2$ *COVID-19 Cases* $+ \beta_3$ *Essential Industries* $+ \beta_4$ *Arts and Recreation* $+ \beta_5$ *Physical Proximity* $+ \beta_6$ *Computer Occupations* $+ \beta_7$ *Population Density* $+ \beta_8$ *Past Growth*

In addition to the regional characteristics shown above, the regression models also include variables that indicate the state of location.[11] The dummy variables control for differences across states in terms of COVID-19 regulations and measures to address the pandemic, and other characteristics of states that might impact metropolitan area employment change. To examine the economic performance of U.S. metros in the periods before, during, and after the COVID-19 shock, we analyze year-over-year employment change over the 12 months of 2020.

The explanatory variable of key interest in the regression analysis is the *New Urban Crisis* measure, which is an index of wage and income inequality, housing unaffordability, and residential segregation. We expect to find a negative relationship between the year-over-year employment change of U.S. regions and the *New Urban Crisis Index*, particularly during the "early recovery" months. The channels by which elements of the new urban crisis might impact a region's recovery and resilience to the COVID-19 economic shock are shown in Figure 5. The left side of the figure shows some of the regional economic impacts of COVID-19 and characteristics of the new urban crisis are shown on the right. In the

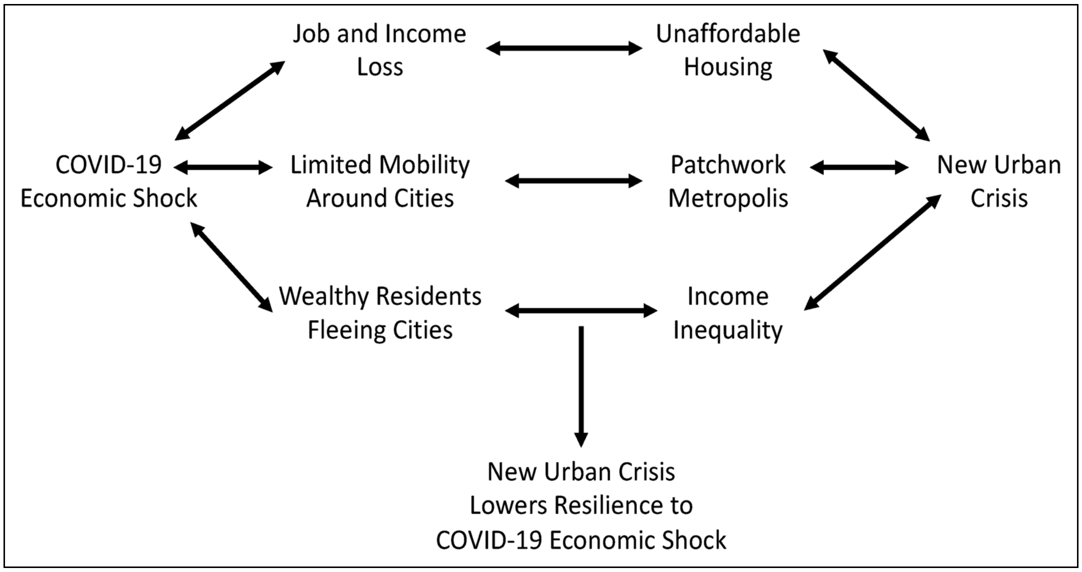

Figure 5. How the new urban crisis lowers a region's resilience to the COVID-19 economic shock.

middle of the figure, the regional economic impacts of COVID-19 interact with elements of the new urban crisis to lower the resilience of regions during the early recovery (in some regions) months.

Perhaps the most visible economic impact of COVID-19 is the job and income loss experienced by workers and households. As noted above, U.S. employment fell by15.2% between April of 2019 and 2020, and about 19% of U.S. metropolitan areas experienced year-over-year employment declines of more than 20%. The loss of jobs and income may be especially problematic in places with high housing costs, where households needed to make larger reductions to their discretionary spending. A second economic impact of COVID-19 is the reduced mobility around regions and restrictions to the use of public transportation (Gkiotsalitis & Cats, 2021; Jenelius & Cebecauer, 2020; Wielechowski et al., 2020). A common side effect of residential segregation, connected to the new urban crisis, is a "patchwork metropolis" where some neighborhoods have residential housing and a mix of service and retail businesses, while other neighborhoods have (mostly) low-cost housing and less access to retail stores and services (Florida, 2017). The limits to public transportation in some places, combined with high levels of residential segregation, may diminish a region's resilience in the face of the COVID-19 shutdown and pandemic.

A third channel by which elements of the new urban crisis may interact with the COVID-19 economic shock to reduce the resilience of regions is through high income and wage inequality. Regions with high levels of inequality are typically characterized by a small middle class, and a bimodal distribution of income with a relatively small segment of high-income earners and a larger group of lower-income earners. The COVID-19 economic shock impacted low-income workers and households more so than those with higher incomes (Chetty et al., 2020; Couch et al., 2020; Lee et al., 2021; Mongey et al., 2021), and studies show differential impacts on mobility (and the ability to leave a city) related to socioeconomic characteristics (Coven & Gupta, 2020; Sy et al., 2021). These disparities in the impacts of COVID-19 across socioeconomic groups might result in lower resilience in regions with greater levels of inequality.

The regression model includes variables that represent the severity of a region's COVID-19 outbreak, a region's industry and occupational structure, population density, and the past growth of regions. As a measure of the severity of a region's COVID-19 outbreak, the regression analysis controls for a metropolitan area's number of COVID-19 cases per capita (i.e., per 100,000 residents). The number of COVID-19 cases is counted as of the day immediately before the month of analysis. For example, the analysis of employment change between June 2019 and 2020 uses information on the number of COVID-19 cases per capita as of May 31, 2020.[12]

To control for a region's industry and occupational structure, the regression analysis accounts for a metropolitan area's share of employment in essential industries. This variable is constructed using County Business Patterns data from 2018 and it uses essential worker classifications from Kane and Tomer (2021). Across all 347 metros, the median share of employment in essential industries is 42%, with a range from 18% to 63% of a metropolitan area's employment. In addition, the regression model includes a variable that measures a region's percentage of total employment in arts and recreation (NAICS 71), which also uses data from County Business Patterns. COVID-19 had particularly large impacts on arts, recreation, and hospitality (Chetty et al., 2020), so we expect to find a negative relationship between the employment change of regions during the months of the COVID-19 pandemic and the share of employment in arts and recreation.

The regression model also controls for a metropolitan area's share of the workforce in occupations that involve close physical proximity. Information on this regional characteristic of the workforce is from the Occupational Information Network (O*NET) of the U.S. Department of Labor. For the work context characteristic of "Physical Proximity," O*NET reports an index score where values of 75 or higher indicate jobs that have workers within an arm's length. These occupations are counted as requiring close physical proximity (Famiglietti et al., 2020), and we matched information from O*NET to metropolitan area workforce numbers using data from 2018 Occupational Employment Statistics of the U.S. Bureau of Labor Statistics. Gabe and Florida (2021) found that the percentage of industry employment in occupations that involve close physical proximity had a negative impact on U.S. industry employment growth rates during the months of April to September of 2020, but not in the period prior to the pandemic.

In addition, the regression analysis considers the influence of computer-related occupations in a metropolitan area. This variable is constructed using data from the 5-year sample of the 2019 American Community Survey of the U.S. Census Bureau. The occupational category used is the share of the workforce in the broad category of Computer and Mathematical Occupations (SOC 15-0000). This variable accounts for a region's ability to pivot to remote work because of the COVID-19 outbreak, as Dingel and Neiman (2020) noted that "100%" of the jobs in the Computer and Mathematical category are "teleworkable." Along with capturing the extent to which people can work from home, the share of a metropolitan area's workforce in Computer and Mathematical occupations is also an indicator of a region's human capital and creative economy. For example, the correlation between the share of employment in Computer and Mathematical occupations and a metropolitan area's college attainment rate is $r = 0.78$, and the correlation with the share of the workforce in creative occupations is $r = 0.83$.[13]

The final two control variables used in the regression model are population density and the past employment growth of metropolitan areas in the years prior to 2019. Population density, which is measured using a weighted density variable proposed by Abel et al. (2012), accounts for differences in the impacts of COVID-19 between dense and sparsely settled metropolitan areas (Hamidi et al., 2020). The past growth of metropolitan areas focuses on the percentage change in employment between 2011 and 2019. The exact month used to construct the past growth variable lines up with the same period analyzed in the dependent variable. For example, the analysis of year-over-year employment growth between January 2019 and 2020 uses past growth between January 2011 and 2019 as an explanatory variable.

The regression results are likely to differ across the months of 2020. For example, during the COVID-19 shutdown period of April and May of 2020, we expect the essential industries and physical proximity variables to be especially important predictors of year-over-year employment change. Specifically, we expect to find a positive relationship between employment growth rates in April and May and the share of employment in essential industries, and a negative relationship between employment growth and the percentage of a metro's workforce in occupations that require close physical proximity. These results are expected due to the widespread COVID-19 restrictions during the shutdown period (e.g., encouraging social distancing) and closure of many nonessential businesses.

The share of a metropolitan area's workforce in computer-related jobs is expected to have a positive association with year-over-year employment growth in all 12 months of 2020, although this characteristic of metropolitan areas may be especially important during the COVID-19 shutdown and early months of the pandemic. The relationship between year-over-year employment change in the pre-pandemic period and computer-related occupations is likely a reflection of the importance of technology and human capital to the growth of regions. As noted above, there's a very high correlation ($r = 0.78$) between the share of employment in Computer and Mathematical occupations (SOC 15-0000) and the share of residents aged 25 and older with at least a 4-year college degree. In the months of the shutdown and early parts of the pandemic, the share of computer-related occupations in a metropolitan area remains a measure of the human capital and technology use in a region, but it also represents a place's ability to pivot to remote working arrangements during the pandemic.[14]

Table 1 presents definitions and descriptive statistics of the variables used in the regression analysis. The first 12 variables listed in the table are the dependent variables that measure the growth of U.S. metropolitan areas in the pre-pandemic months (i.e., January to March), the COVID-19 shutdown and early pandemic months, and the months at the end of 2020 when some places started to recover from the economic impacts of COVID-19. The rest of the variables shown in Table 1 are used as explanatory variables in the analysis of the year-over-year employment change of U.S. metropolitan areas. For example, Florida's (2017) *New Urban Crisis Index* ranges from 0.062 to 0.978 for the metros in our analysis, with a mean value of 0.505. The COVID-19 case number variables show a dramatic increase in cases over the first few months of the pandemic. The descriptive statistics show an average of about 42% of a metropolitan area's employment in essential industries and about

Table 1. Variable Definitions and Descriptive Statistics.

Variable	Definition	Mean	Standard deviation	Min.	Max.
January employment change	Jan. 2019 to 2020 employment growth rate	0.009	0.016	−0.054	0.049
February employment change	Feb. 2019 to 2020 employment growth rate	0.009	0.016	−0.049	0.053
March employment change	Mar. 2019 to 2020 employment growth rate	0.000	0.016	−0.068	0.044
April employment change	Apr. 2019 to 2020 employment growth rate	−0.155	0.051	−0.375	−0.047
May employment change	May 2019 to 2020 employment growth rate	−0.125	0.050	−0.406	0.002
June employment change	Jun. 2019 to 2020 employment growth rate	−0.089	0.043	−0.383	0.012
July employment change	Jul. 2019 to 2020 employment growth rate	−0.077	0.036	−0.238	0.025
August employment change	Aug. 2019 to 2020 employment growth rate	−0.072	0.035	−0.236	0.026
September employment change	Sept. 2019 to 2020 employment growth rate	−0.064	0.035	−0.280	0.032
October employment change	Oct. 2019 to 2020 employment growth rate	−0.058	0.034	−0.253	0.045
November employment change	Nov. 2019 to 2020 employment growth rate	−0.058	0.033	−0.223	0.076
December employment change	Dec. 2019 to 2020 employment growth rate	−0.059	0.036	−0.215	0.101
New Urban Crisis Index	Index measuring income and wage inequality, housing unaffordability, and residential segregation (by income, educational attainment, and occupation), Florida (2017)	0.505	0.215	0.062	0.978
COVID-19 cases, February	Cases per 100,000 population on 1/31/20	0.000	0.003	0.000	0.050
COVID-19 cases, March	Cases per 100,000 population on 2/29/20	0.039	0.265	0.000	2.698
COVID-19 cases, April	Cases per 100,000 population on 3/31/20	17	27	0	309
COVID-19 cases, May	Cases per 100,000 population on 4/30/20	166	213	7	1,947
COVID-19 cases, June	Cases per 100,000 population on 5/31/20	346	381	18	3,170
COVID-19 cases, July	Cases per 100,000 population on 6/30/20	570	494	33	3,700
COVID-19 cases, August	Cases per 100,000 population on 7/31/20	1,119	753	93	5,100
COVID-19 cases, September	Cases per 100,000 population on 8/31/20	1,601	975	148	5,880
COVID-19 cases, October	Cases per 100,000 population on 9/30/20	2,047	1,106	167	6,558
COVID-19 cases, November	Cases per 100,000 population on 10/31/20	2,728	1,325	198	8,733
COVID-19 cases, December	Cases per 100,000 population on 11/30/20	4,275	1,910	539	12,742
Essential industries	Employment share in essential industries, Kane and Tomer (2021)	0.418	0.063	0.176	0.626
Arts and recreation	Employment share in Arts, Entertainment, and Recreation (NAICS 71—-) Sector	0.017	0.008	0.002	0.069
Physical proximity	Employment share in occupations that have workers within an arm's length	0.262	0.034	0.139	0.396
Computer occupations	Employment share in Computer and Mathematical occupations (SOC 15-0000)	0.024	0.013	0.006	0.118
Population density	Weighted population density (people per square mile) (Abel et al., 2012)	1,256	1,364	11	18,551
Past growth, January	Jan. 2011 to 2019 employment growth rate	0.151	0.110	−0.091	0.595
Past growth, February	Feb. 2011 to 2019 employment growth rate	0.151	0.110	−0.091	0.603
Past growth, March	Mar. 2011 to 2019 employment growth rate	0.147	0.110	−0.102	0.582
Past growth, April	Apr. 2011 to 2019 employment growth rate	0.141	0.109	−0.112	0.573
Past growth, May	May 2011 to 2019 employment growth rate	0.141	0.108	−0.099	0.564
Past growth, June	Jun. 2011 to 2019 employment growth rate	0.140	0.109	−0.107	0.551

(continued)

Table 1. (continued)

Variable	Definition	Mean	Standard deviation	Min.	Max.
Past growth, July	Jul. 2011 to 2019 employment growth rate	0.138	0.109	−0.103	0.549
Past growth, August	Aug. 2011 to 2019 employment growth rate	0.137	0.110	−0.101	0.532
Past growth, September	Sept. 2011 to 2019 employment growth rate	0.132	0.109	−0.104	0.546
Past growth, October	Oct. 2011 to 2019 employment growth rate	0.136	0.111	−0.112	0.556
Past growth, November	Nov. 2011 to 2019 employment growth rate	0.139	0.113	−0.112	0.560
Past growth, December	Dec. 2011 to 2019 employment growth rate	0.137	0.112	−0.116	0.560
Housing unaffordability	Median monthly costs of owner-occupied housing (with a mortgage) multiplied by 12, divided by median household income	0.292	0.035	0.221	0.427
Regional Gini coefficient	Gini coefficient of income inequality	0.458	0.024	0.392	0.542
Residential segregation (by income)	Average residential segregation of families in poverty and households with annual incomes over $200,000	0.364	0.052	0.223	0.491
Residential segregation (by education)	Average residential segregation of people with at least a 4-year college degree and people with less than a high school diploma	0.278	0.059	0.131	0.440
Residential segregation (by occupation)	Average residential segregation of people in Creative Class occupations, people in Service Class occupations, and people in Working Class occupations	0.172	0.035	0.092	0.292

Notes: Employment change (private nonfarm employment) figures are from the U.S. Bureau of Labor Statistics; New Urban Crisis Index values are from Florida (2017); COVID-19 case numbers are from the Opportunity Insights database (Chetty et al., 2020); the Essential Industries and Arts and Recreation variables are from 2018 County Business Patterns; the Physical Proximity and Computer Occupation variables are from 2018 Occupational Employment Statistics from the U.S. Department of Labor; Population Density is from Abel et al. (2012); and the Housing Unaffordability, Regional Gini Coefficient and Residential Segregation variables are from the 5-year sample of the 2019 American Community Survey.

Table 2. Factors Affecting Year-Over-Year Monthly Employment Change in U.S. Metropolitan Area: Pre-Pandemic Months of 2020 ($n = 347$).

	January	February	March
New Urban Crisis Index	0.017	0.058	0.037
	(0.069)	(0.070)	(0.071)
COVID-19 cases	NA	−0.091*	−0.031
		(0.049)	(0.071)
Essential industries	0.028	0.021	0.131**
	(0.055)	(0.055)	(0.057)
Arts and recreation	0.091	0.041	0.020
	(0.058)	(0.058)	(0.060)
Physical proximity	0.127**	0.098*	0.077
	(0.056)	(0.056)	(0.058)
Computer occupations	0.183***	0.191***	0.142**
	(0.060)	(0.067)	(0.062)
Population density	0.007	−0.016	−0.036
	(0.056)	(0.056)	(0.058)
Past growth	0.201***	0.215***	0.199***
	(0.061)	(0.062)	(0.065)
State-level dummy variables	Yes	Yes	Yes
R-squared	0.482	0.487	0.450
Adjusted *R*-squared	0.380	0.383	0.340

Notes: Standard errors are shown in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and10% levels. The variables, except for the state-level dummy variables, are transformed into standardized values (i.e., *Z*-scores).

one quarter in occupations where workers are within an arm's length of others. The final five variables shown in Table 1 are individual measures of the new urban crisis, which are used later in the paper to dive deeper into our results related to the *New Urban Crisis Index*. For example, the average (across all 347 metros) 12-month median costs of owner-occupied housing is equivalent to about 30% of median household income, with a range of 0.22 to 0.43.

Regression Results

Table 2 to 4 shows regression results on the factors associated with the year-over-year employment growth of U.S. metropolitan areas for all 12 months of 2020. The analysis uses data on 347 metropolitan areas, which collectively account for 84% of the total U.S. population.[15] The regression models include the explanatory variables described above, as well as a set of dummy variables that indicate a metropolitan area's state of location (see note 11). The state-level dummy variables control for COVID-19 policies that may differ by state, as well as other state-specific factors that might be related to the employment growth of regions. Prior to conducting the regression analysis, we transformed all the variables, except for the state-level dummies, into standardized values (i.e., *Z*-scores) to allow more consistent comparisons across the estimated coefficients.

Focusing on the regression results examining the employment growth of metropolitan areas between January 2019 and 2020, which is prior to the COVID-19 pandemic, the variables included in the regression model explain about 50% (r-squared = 0.482) of the variation in employment growth rates.[16] A metropolitan area's employment growth between January 2011 and 2019 has a positive and statistically significant association with its growth in the following twelve months. Likewise, the share of employment in computer-related jobs and the percentage of a metropolitan area's workforce in occupations requiring proximity to others are positively associated with year-over-year employment growth between January 2019 and 2020.[17] These regression results are generally representative of the factors that are associated with employment change in the three months of 2020 prior to the pandemic (Table 2). Past rates of employment growth and the share of employment in computer-related jobs have a positive and statistically significant association with year-over-year employment change in January, February, and March; and there's a positive and statistically significant relationship between metropolitan area employment growth and the share of employment in jobs requiring close physical proximity in January and February.

Whereas the regression results are largely similar for the three months prior to the pandemic, the regression results changed dramatically during the COVID-19 shutdown and early pandemic period (Table 3). First, the estimated coefficients corresponding with the variables measuring past growth and physical proximity changed from positive and statistically significant prior to the pandemic to negative

Table 3. Factors Affecting Year-Over-Year Monthly Employment Change in U.S. Metropolitan Area: COVID-19 Shutdown and Early Pandemic Months of 2020 ($n = 347$).

	April	May	June	July	August
New Urban Crisis Index	0.000	−0.029	−0.022	−0.057	−0.037
	(0.059)	(0.056)	(0.060)	(0.064)	(0.066)
COVID-19 cases	−0.028	0.036	0.060	0.066	0.009
	(0.053)	(0.050)	(0.051)	(0.050)	(0.058)
Essential industries	0.230***	0.184***	0.108**	0.082	0.056
	(0.047)	(0.044)	(0.049)	(0.052)	(0.053)
Arts and recreation	−0.148***	−0.170***	−0.180***	−0.194***	−0.192***
	(0.050)	(0.047)	(0.051)	(0.054)	(0.055)
Physical proximity	−0.116**	−0.107**	−0.050	0.001	−0.003
	(0.048)	(0.045)	(0.049)	(0.052)	(0.053)
Computer occupations	0.178***	0.161***	0.118**	0.152***	0.124**
	(0.052)	(0.049)	(0.054)	(0.057)	(0.059)
Population density	−0.001	−0.070	−0.123**	−0.147***	−0.132**
	(0.057)	(0.053)	(0.054)	(0.055)	(0.055)
Past growth	−0.139**	−0.081	−0.075	−0.074	−0.058
	(0.054)	(0.052)	(0.056)	(0.060)	(0.062)
State-level dummy variables	Yes	Yes	Yes	Yes	Yes
R-squared	0.622	0.664	0.601	0.555	0.539
Adjusted *R*-squared	0.545	0.596	0.521	0.465	0.446

Notes: Standard errors are shown in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels. The variables, except for the state-level dummy variables, are transformed into standardized values (i.e., *Z*-scores).

Table 4. Factors Affecting Year-Over-Year Monthly Employment Change in U.S. Metropolitan Area: COVID-19 Recovery (in Some Places) Months of 2020 ($n = 347$).

	September	October	November	December
New Urban Crisis Index	−0.071	−0.120	−0.180**	−0.165**
	(0.069)	(0.073)	(0.072)	(0.068)
COVID-19 cases	0.022	0.017	0.034	0.060
	(0.066)	(0.070)	(0.071)	(0.076)
Essential industries	0.063	0.068	0.072	0.076
	(0.055)	(0.057)	(0.056)	(0.054)
Arts and recreation	−0.122**	−0.077	−0.050	−0.047
	(0.058)	(0.061)	(0.060)	(0.058)
Physical proximity	0.057	0.073	0.060	0.031
	(0.055)	(0.058)	(0.057)	(0.055)
Computer occupations	0.143**	0.105	0.098	0.095
	(0.063)	(0.065)	(0.065)	(0.062)
Population density	−0.157***	−0.155**	−0.168***	−0.162***
	(0.057)	(0.059)	(0.058)	(0.056)
Past growth	−0.109	−0.038	0.005	0.021
	(0.065)	(0.068)	(0.068)	(0.065)
State-level dummy variables	Yes	Yes	Yes	Yes
R-squared	0.495	0.452	0.465	0.506
Adjusted *R*-squared	0.393	0.342	0.357	0.407

Notes: Standard errors are shown in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels. The variables, except for the state-level dummy variables, are transformed into standardized values (i.e., *Z*-scores).

and statistically significant in the analysis of employment change between April 2019 to 2020; physical proximity is negatively associated with year-over-year employment change in May as well. The negative relationship between April 2019 to 2020 employment change and the past growth of metropolitan areas, compared with the regression results focusing on months prior to the pandemic, suggests that the general patterns of metropolitan area employment growth changed because of the pandemic. The negative relationship between physical proximity and year-over-year employment change in April and May, compared with a positive relationship in January and February, is consistent with the COVID-19 measures that encouraged social distancing.

The regression results pertaining to the essential industries and arts and recreation variables also changed substantially between the pre-pandemic period and the months of the COVID-19 shutdown and early pandemic. There's a positive and statistically significant relationship between year-over-year employment change and the share of a region's employment in essential industries from April to June, and the estimated coefficient increased from 0.131 to 0.230 between March and April. This result is likely explained, at least in part, by the fact that essential businesses were allowed to remain open at the beginning of the pandemic. Whereas the percentage of employment in arts and recreation was unrelated to the employment growth of U.S. regions prior to the pandemic, this variable had a negative and statistically significant association with year-over-year employment change from April to September of 2020. For example, a one standard deviation increase in a metro's share of employment in arts and recreation is associated with a 0.17 standard deviation decrease in year-over-year employment change in May of 2020. These results generally show that the types of industries present in a region influenced economic performance during the COVID-19 shutdown and early pandemic.

Other results show that the share of employment in computer occupations had a positive and statistically significant association with year-over-year employment change throughout the entire COVID-19 shutdown and early pandemic period. These findings are consistent with workers in computer occupations enabling a region's workforce to work remotely and, to some extent, also reflect the importance of a region's human capital to economic performance throughout the crisis. During the pandemic months of June to August and continuing through the early parts of the recovery

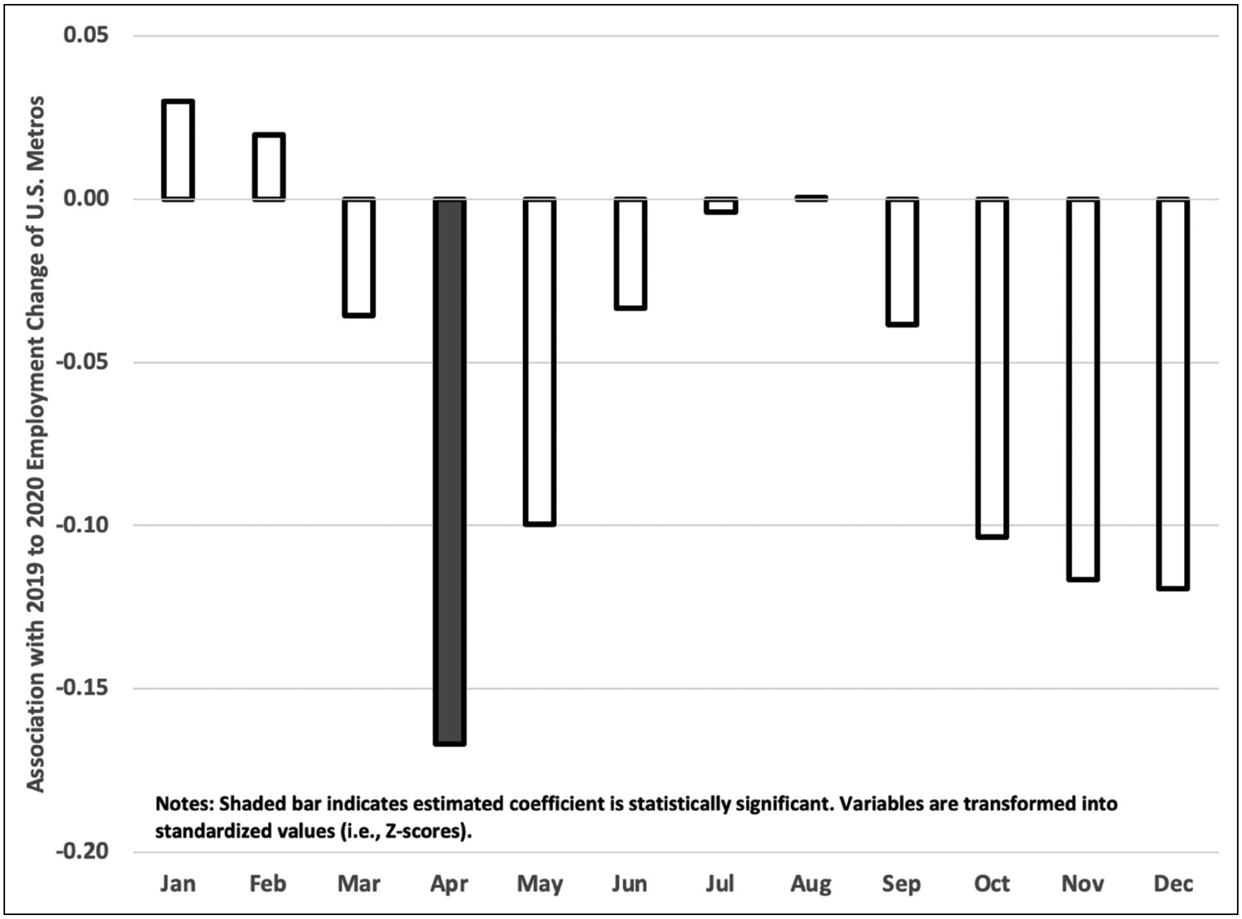

Figure 6. Housing unaffordability and the 2019 to 2020 employment change of U.S. metros.

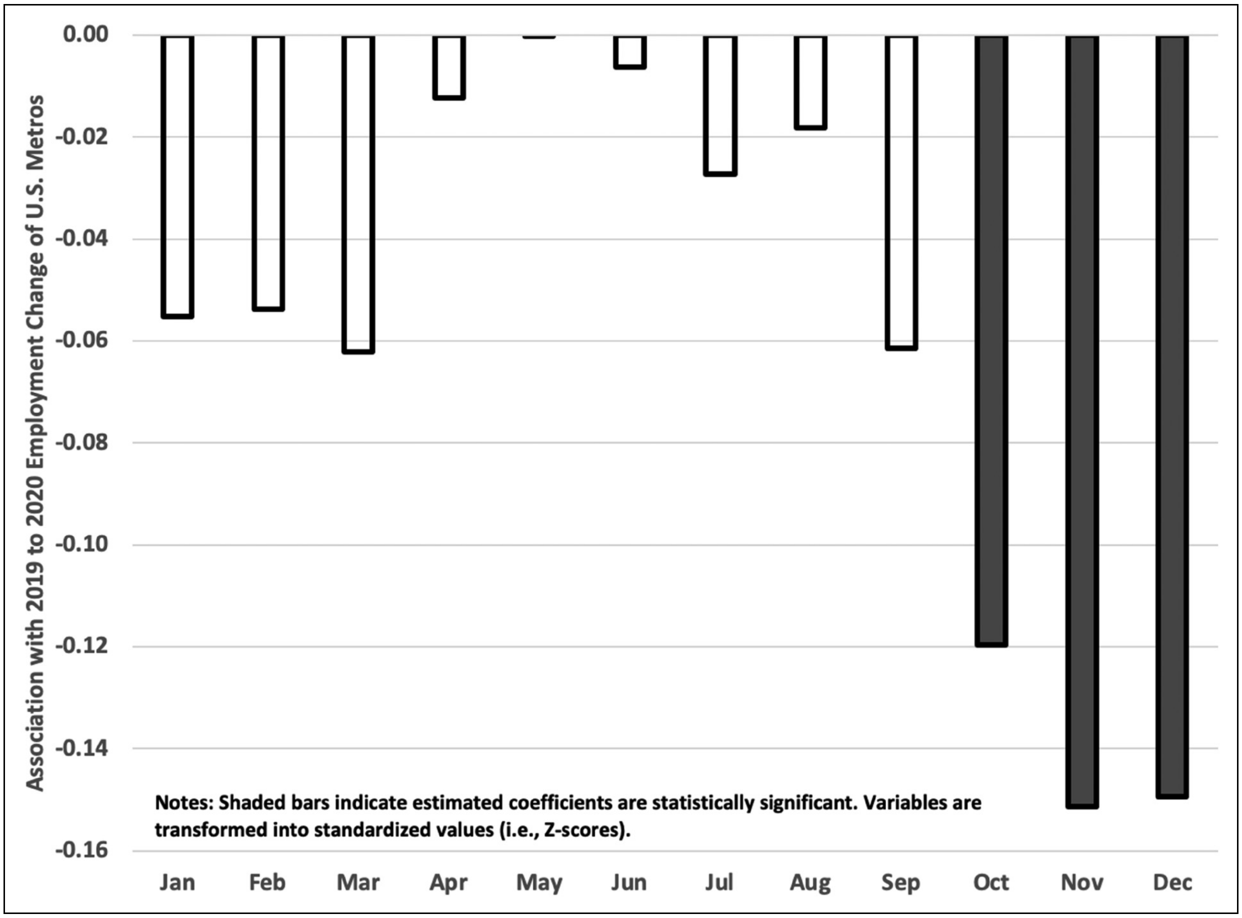

Figure 7. Regional Gini coefficient and the 2019 to 2020 employment change of U.S. metros.

from September to December of 2020, the population density of metropolitan areas had a negative and statistically significant association with year-over-year employment change.[18] This could be interpreted to mean that the pandemic had a larger economic impact on more densely populated areas, and that having a more sparsely populated area aided in a region's recovery from the COVID-19 economic shock.

After not having a statistically significant association with metropolitan area employment change from January to October of 2020, the *New Urban Crisis Index* had a negative impact on the performance of regions during the early recovery months of November and December. This regional measure, along with population density, are the only two variables that have a statistically significant association with the performance of metropolitan areas in November and December. The estimated coefficients corresponding with the *New Urban Crisis Index* in these two months suggest that a one standard deviation increase in this composite indicator of regional inequality and segregation is associated with about a 0.17 standard deviation decrease in year-over-year employment growth. The magnitudes of these impacts are like the results pertaining to the share of employment in the arts and recreation sector during the COVID-19 shutdown and early months of the pandemic. Overall, the negative relationship between year-over-year employment change at the end of 2020 and this indicator of the new urban crisis suggests that regional characteristics such as high housing costs, residential segregation, and income and wage inequality hampered the resilience of regions at recovering from the employment declines related to the COVID-19 economic shock.

To delve deeper into the aspects of the new urban crisis that affected the employment recovery of U.S. regions in response to the COVID-19 economic shock, we estimated five additional versions of the regression models after replacing the *New Urban Crisis Index* with individual components that make up the composite indicator. These results are summarized in Figures 6 to 10, where the bars indicate the values of the estimated coefficients corresponding to the selected component of the index and they are shaded when the estimated coefficient is statistically significant at 10% or lower.

In Figure 6—after controlling for all the variables shown in Table 2 (except for the *New Urban Crisis Index*)—we see that the percentage of a metro's median household income devoted to the twelve-month median costs of owner-

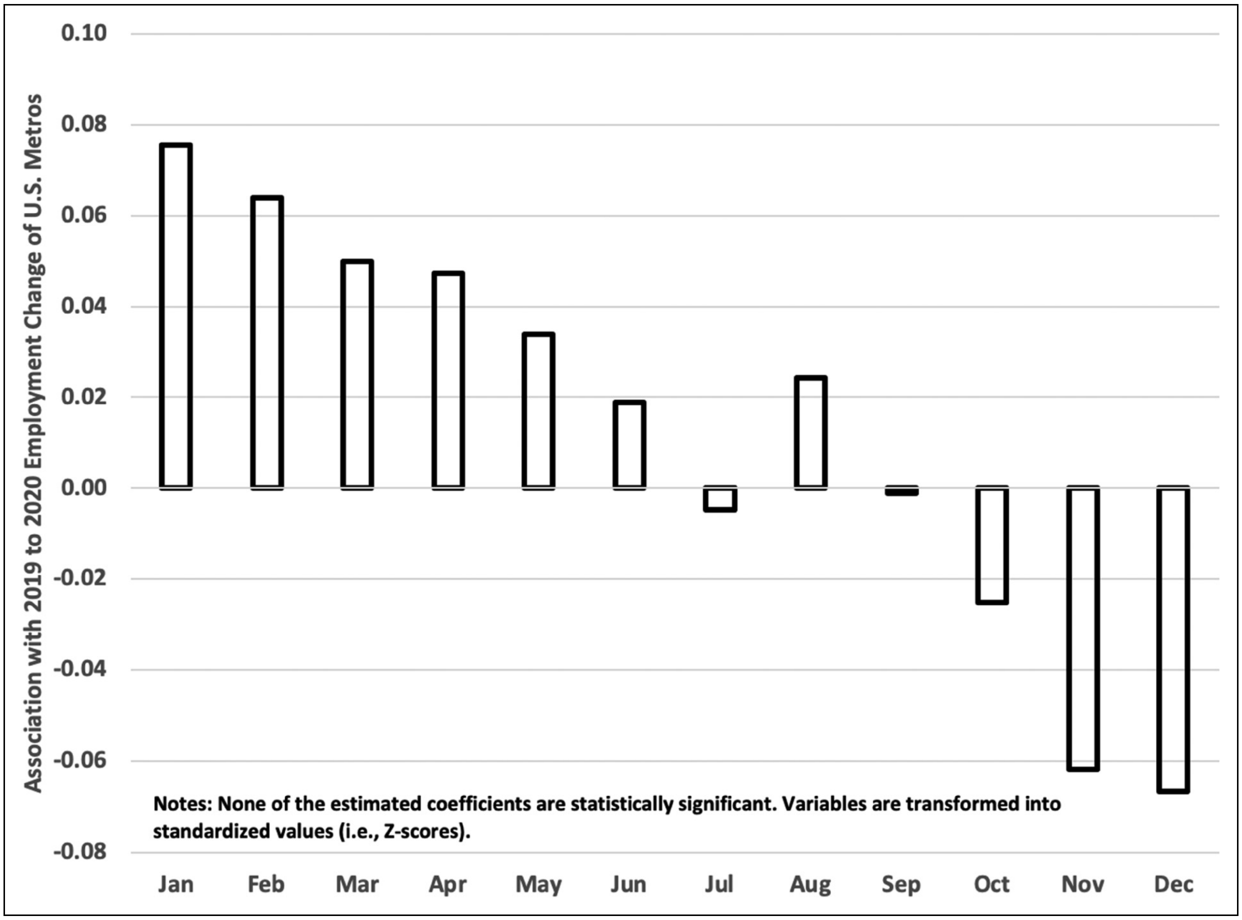

Figure 8. Residential segregation (by income) and the 2019 to 2020 employment change of U.S. metros.

occupied housing has a negative and statistically significant association with year-over-year employment change in April of 2020. The results suggest that, whereas housing unaffordability is negatively associated with the economic performance of U.S. metropolitan areas during the immediate shutdown at the start of the pandemic, housing costs did not have a statistically significant association with metro employment change in the early pandemic months after April or during the recovery (in some regions) months later in 2020. An explanation for this result is that mortgage forbearance programs and other income and housing support initiatives implemented near the beginning of the pandemic insulated regional economic conditions from the impacts of high housing costs.

The results summarized in Figure 7 show that high regional income inequality, as measured by the Gini coefficient, is negatively associated with year-over-year employment change in the COVID-19 recovery months of October, November, and December. Given that a region's ability to recover from large economic shocks is a sign of resilience, these results suggest that high levels of income inequality, a key indicator of the new urban crisis, hurt the resilience of regions to the economic impacts of COVID-19. The results presented in Figures 8 to 10 show that the year-over-year employment change of U.S. metros in the COVID-19 recovery months at the end of 2020 is negatively associated with high levels of residential segregation by educational attainment and broad occupational group. Our findings also indicate a negative relationship between employment growth and high residential segregation by educational attainment (Figure 9) in the early pandemic months of June and July of 2020, and the regression analysis does not reveal a statistically significant relationship between employment change and the residential segregation of households by income (i.e., families in poverty and households with annual incomes of $200,000 or more).

Overall, the results presented in Figures 6 to 10 suggest that our baseline findings related to the *New Urban Crisis Index* are largely driven by measures of regional income inequality and residential segregation. Whereas high housing costs relative to incomes are negatively associated with economic performance during the COVID-19 shutdown in April 2020, these results dissipate in later months. This means that aspects of the new urban crisis with the largest negative association with the (employment) resilience of U.S. metropolitan areas are those that cannot be addressed with a financial

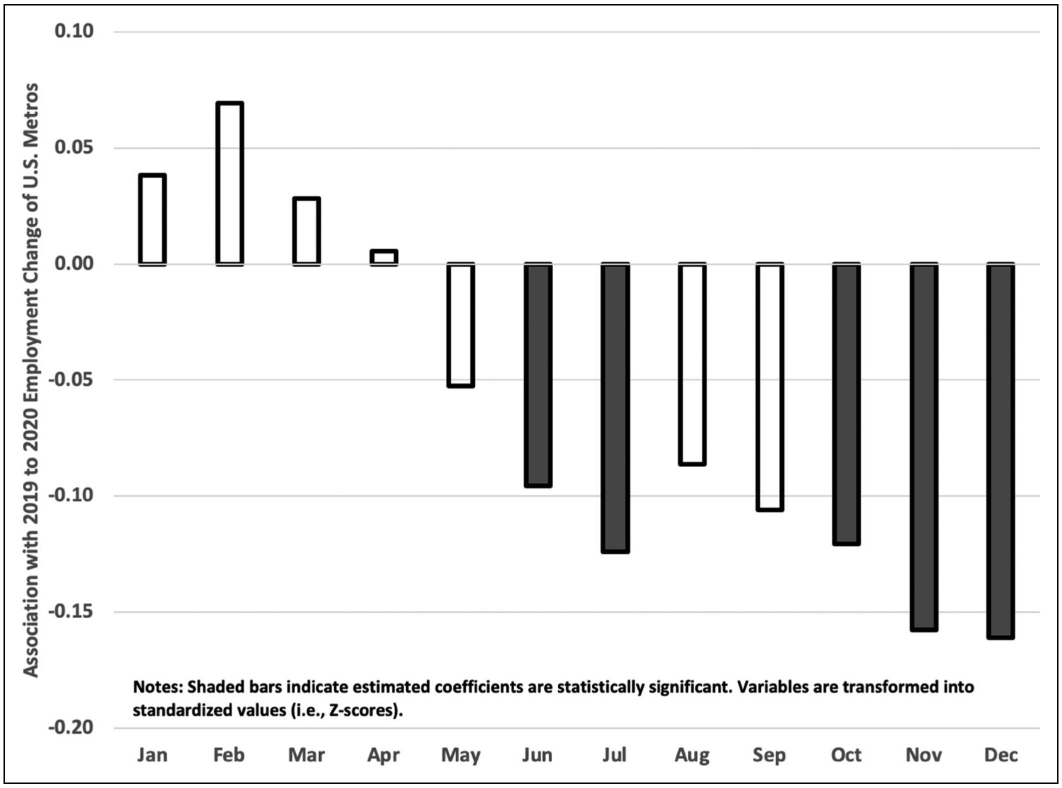

Figure 9. Residential segregation (by education) and the 2019 to 2020 employment change of U.S. metros.

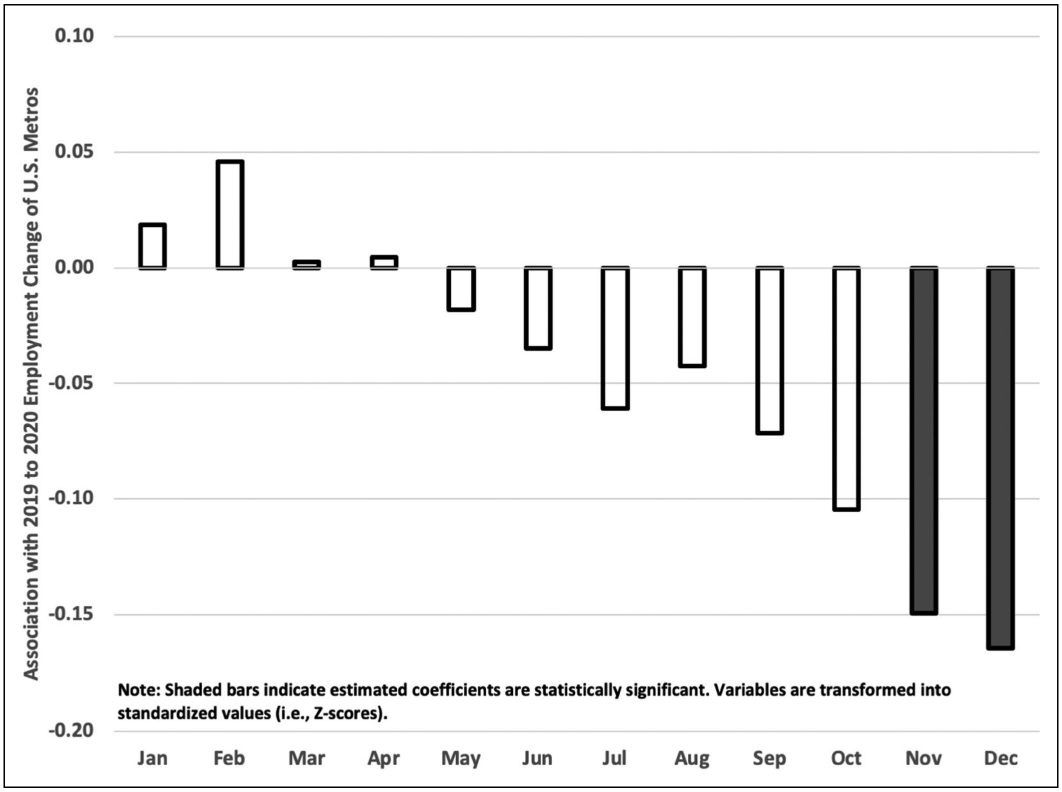

Figure 10. Residential segregation (by occupation class) and the 2019 to 2020 employment change of U.S. metros.

stimulus or other sort of immediate action. Whereas the problem of housing unaffordability can be impacted (in the short run) through mortgage forbearance programs or direct subsidies to households, the problems of income inequality and residential segregation do not have a quick fix.

Conclusions

Along with very large and serious impacts on health and overall well-being, the COVID-19 pandemic led to a very large, worldwide economic shock. U.S. employment fell by 15% between March and April of 2020, and year-over-year employment between April 2019 and 2020 fell by more than 20% in 19% of U.S. metropolitan areas. The COVID-19 pandemic resulted in an almost immediate reshuffling of the deck in terms of the employment growth of U.S. metropolitan areas. Regions that grew faster between 2011 and 2019 experienced larger employment declines between April 2019 and 2020. The types of industries (e.g., essential businesses, arts, and recreation) and occupations (e.g., close physical proximity, computer-related jobs) in a region were also associated with the year-over-year employment change of U.S. metropolitan areas during the COVID-19 shutdown and early months of the pandemic.

By the fall of 2020, some regions were starting to recover from the negative economic impacts of COVID-19. Other things being equal, the relative economic performance of regions during the fall of 2020 provides evidence on the ability of regions to adapt to and recover from the COVID-19 economic shock. Here, we find that U.S. metropolitan areas that rate worse for the new urban crisis saw lower employment growth rates in November and December of 2020 than places that were less adversely impacted by the new urban crisis. Further analysis into these results shows that our measures of income inequality and residential segregation by educational attainment and broad occupational group are negatively associated with the growth of U.S. metros at the end of 2020. These results provide some evidence that a combination of a residential location pattern of a patchwork metropolis combined with limited mobility around cities due to COVID-19, as well as a mix of income inequality and higher-income residents leaving cities due to COVID-19, are associated with lower economic resilience during the pandemic. On the other hand, high costs of housing (relative to incomes) appear to be unrelated to the employment change of U.S. metros at the end of 2020, presumably due to a variety of government programs that helped households.

Future research can analyze the effects of the new urban crisis and its individual components on how individual people coped during the COVID-19 pandemic using micro data files to uncover a more decisive mechanism by which the new urban crisis affected the employment change of regions before and through the pandemic. Likewise, future research can examine the patterns of employment change deeper into the COVID-19 recovery (e.g., spring and summer of 2021, and beyond) to examine the more lasting impacts of the new urban crisis on the resilience of regions. Additional avenues of fruitful research could be a comparison of the factors—including additional regional characteristics such as race, ethnicity, and expanded measures of human capital—that affected economic change because of COVID-19 to the characteristics of regions that affected economic conditions during other recessions.

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ORCID iD

Todd Gabe https://orcid.org/0000-0002-9455-2070

Notes

1. Some of the income inequality that characterizes the new urban crisis is due to the growth of low-income jobs driven by the demand for services and goods by knowledge and high human capital workers (Florida, 2017).
2. Data on the number of COVID-19 cases are from the Opportunity Insights database (Chetty et al., 2020).
3. Employment figures are from the Current Employment Statistics series of the U.S. Bureau of Labor Statistics.
4. Similarly, Pike et al. (2010, p.59) define resilience as a region's ability to respond, "to an evermore diverse array of external shocks and transitions, including financial crises, dangerous climate change, terror campaigns and extreme weather events."
5. Employment growth provides a relatively narrow view of resilience in that employment growth does not always translate into an increase in economic development (Gabe, 2017) and it's not a measure of inclusive growth. Future research can develop broader measures of resilience (perhaps related to the response of local governments and residents to COVID-19) and examine the recovery of U.S. regions over a longer time frame.
6. All of the residential segregation variables use data from the 5-year sample of the 2019 American Community Survey.
7. In addition to residential segregation by income, education, and occupation, which are considered in Florida's (2017) *New Urban Crisis Index* and used in this research, regions are also characterized by residential segregation along the lines of race, ethnicity, and other features. Future research can focus on the connections between these and other types of residential segregation and the impacts of segregation on other regional indicators.
8. Employment and unemployment figures are from the U.S. Bureau of Labor Statistics.
9. According to the Economic Tracker of Opportunity Insights, employment levels of high-wage workers were only 1.2% below pre-pandemic levels as of June 1, 2020, whereas employment of low-wage workers was 24.5% lower than before COVID-19 (Chetty et al., 2020).

10. The analysis focuses on private nonfarm employment, which is highly correlated with total nonfarm employment. For example, the correlation across U.S. metropolitan areas between year-over-year total nonfarm employment growth and year-over-year private nonfarm employment growth is r=0.96 or more in eight of the twelve months of 2020.
11. About 12% of the metropolitan areas cross state borders. These regions are assigned to their primary state of location (i.e., the first state listed by the U.S. Census Bureau). For example, Virginia Beach is assigned to Virginia, Chicago is assigned to Illinois, Louisville is assigned to Kentucky, Charlotte is assigned to North Carolina, and Philadelphia is assigned to Pennsylvania.
12. Along with the number of COVID-19 cases, the number of deaths attributed to COVID-19 is also an indicator of the severity of a region's health crisis. These two variables, however, are highly correlated. For example, the correlation between the number of COVID-19 cases and deaths per 100,000 residents, as of April 30, 2020, is r=0.87. The correlation between COVID-19 cases and deaths would likely be even higher if deaths were measured with a several-week lag after when cases were measured.
13. Computer and Mathematical Occupations are one of the broad occupational groups counted in the Creative Class (Florida, 2002).
14. For example, as noted above, Dingel and Neiman (2020) found that 100% of the jobs in this broad occupational category (SOC 15-0000) are teleworkable.
15. Population data are from the 5-year sample of the 2019 American Community Survey.
16. In a regression model that only includes the state-level dummy variables, the r-squared and adjusted r-squared values are 0.382 and 0.278. In a regression model that includes all the variables except for the *New Urban Crisis Index*, the r-squared and adjusted r-squared values are 0.482 and 0.382. These values are practically identical to the r-squared and adjusted r-squared values reported in Table 2a (0.482 and 0.380), which is expected because the *New Urban Crisis Index* does not have a statistically significant association with January 2019 to 2020 employment change.
17. Given the potential importance of public-sector jobs to the employment resilience of regions, we also estimated a version of the model that included as an additional explanatory variable the percentage of employment in government jobs. This variable does not have a statistically significant relationship with year-over-year employment change in any of the twelve months of 2020.
18. We estimated different versions of the model that use a variable for metropolitan area population size instead of density, which are highly correlated (r = 0.80). The population size of a metropolitan area has a negative and statistically significant relationship with year-over-year employment change in July of 2020, and the estimated coefficient is statistically insignificant in the other eleven months considered in the analysis.

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Author Biographies

Richard Florida is university professor in the University of Toronto's Rotman School of Management and School of Cities.

Todd Gabe is a professor of economics at the University of Maine.