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Broadly Shared Local Economic Success Since 2000: New Measures and New Lessons for Communities

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Abstract

In recent decades, many local labor markets—especially those in former industrial areas—have experienced lagging employment rates, hourly wages, and annual earnings. Even in places that have thrived, disadvantaged racial and ethnic groups and those with less education have often fared poorly, and long-term growth has bypassed many Americans at the middle and bottom of the income distribution. This report examines the relative economic success over the past two decades (prior to the COVID pandemic) of different local labor markets throughout the United States, both for residents overall and for those of different demographic groups. We construct a new, **publicly available database** for economic indicators for these labor markets—both commuting zones and core-based statistical areas—for each of 160 demographic cells and three time periods. Our economic indicators account for demographic and cost-of-living differences across areas, facilitating comparisons of economic trends across geographies for different groups of interest. We show that locations that have performed well in terms of employment growth have not always performed well in terms of earnings growth; moreover, areas that have seen broad growth overall for their residents have often seen growth lag for vulnerable groups. To more systematically understand factors associated with economic success for different groups, we examine the relationship with baseline correlates and supplement these descriptive regressions with insights from narrative case studies. Although initial industry mix plays an important role, other factors, including government investment and local leadership, may matter even more.

JEL Classification Codes: I31, J31, R11, R23

Key Words: earnings growth, local labor markets, geographic inequality, demographics, cost of living, commuting zones, metropolitan areas

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1. INTRODUCTION

This report examines the relative economic success over the past two decades of different local labor markets throughout the United States, both for residents overall and for those of different demographic groups. We define economic success primarily as the growth since 2000 in real annual earnings per person, although we also consider growth in employment rates and real hourly wage rates.

What motivates this project? In part, the impetus is increased disparity in labor market outcomes across areas. In recent years, many labor markets—especially those in former industrial areas—have experienced lagging employment rates, hourly wages, and annual earnings. Even in high-tech cities that have thrived, such as San Francisco, disadvantaged racial and ethnic groups and those with less education have often fared poorly.

These issues are not just regional but often national in scope. Although many Americans have experienced considerable growth in real incomes since 2000, this long-term growth has bypassed many Americans at the middle and bottom of the income distribution, as well as racially disadvantaged groups such as African Americans. While it is encouraging that the recovery from the pandemic and strong labor market have helped counter these longer-term trends, these changes have only partly offset the previous trajectories, and it is unclear whether they will last through the next recession or revert back.

Moreover, the adverse trends for disadvantaged groups do not have fully understood causes. It is important not only to better understand what shapes them, but also to devise effective solutions: How can we make economic opportunity more broadly available? Potential solutions to promoting "inclusive growth" may lie in the experience of local areas that have outperformed expectations in achieving labor market success for multiple demographic groups. This potential for greater understanding of both causes and solutions to these labor market problems is the rationale for this this report and its accompanying database.

To begin our examination, we first describe how indicators for labor market success evolved for different local labor markets between 2000 and the years immediately preceding the pandemic. Because our trend analysis controls for both local prices and the detailed demographic mix of residents, we are better able to compare "apples with apples"—that is, making our comparisons consist of similar individuals even across diverse local labor markets. We place a special focus on trends for groups that are economically disadvantaged, including persons with less than a bachelor's degree, and Black and Hispanic individuals.

We next correlate these trends with possible economic and social determinants. This correlational analysis allows us to address questions such as: to what extent are the good fortunes of some local labor market due to its having a large presence in rapidly growing and/or high-wage industries? How important are the local area's share of highly educated residents, or its composition of different demographic groups, including age? Do these factors matter differently for some demographic groups more than others, and what factors, if any, predict broadly shared economic growth?

Using these regression results, we then explore to what extent we can explain most areas' fortunes. After accounting for the observable factors, some areas are outliers, having trends in real earnings or other success indicators that exceed or fall short of expectations. What areas do better or worse than expected, after controlling for economic and social determinants?

Based on this regression and outlier analysis, our examination then presents a synthesis from illustrative case studies. We generally compare local labor markets that appear similar at baseline, and we explore through narratives what events may plausibly have explained relative economic trends. These case studies, informed by the regression and outlier analysis, provide a model for other comparisons that applied researchers may choose to perform with our database, which we also describe and provide details for accessing.

In Section 7 we provide a brief description of our database, which is publicly available, to facilitate its use by other researchers and policy makers wishing to carefully assess and compare trends of local labor market success. Finally, we conclude with some formative lessons learned from our combined exercises, and how superficial comparisons that do not account for important contextual differences can yield an incomplete—or even inaccurate—picture of which areas have been succeeding and why.

Executive Summary of How We Define Local Labor Market Success and What We Find

To measure success, this report uses data across hundreds of U.S. labor markets from the 2000 Census of population and annual American Community Surveys (ACS). Specifically, the report focuses on three time periods, each of which is at or near an economic peak: 2000, 2005–2007, and 2015–2019. The first is captured by the Population Census and the latter two are measured from the ACS, for which we use multi-year averages to increase sample size and precision. We define local labor markets based on "commuting zones" (CZs), which are multi-county areas that encompass most commuting flows and collectively span the entire country.[1] For reasons of data accuracy and practicality, we focus on CZs with at least 100,000 population

[1] We have also conducted analyses using as local labor markets Core-Based Statistical Areas (CBSAs), which are defined by the Office of Management and Budget and typically consist of multi-county areas with an urbanized center and surrounding areas that are socioeconomically integrated. CBSAs encompass 84 percent of the U.S. population but leave out rural areas, where labor markets may operate differently. The pattern of our results is generally similar for both CZs and CBSAs.

as of 2000. The resulting 371 CZs comprised 96 percent of the total U.S. population that year, and slightly more since.

We measure a CZ's "success" by the change over time in its employment rate, real hourly wage, and real annual earnings, measured both for all residents and for specific demographic groups. Importantly, we adjust wages and earnings not just for inflation but also for local prices, and we further adjust *all three* measures for the CZ's demographic composition by age, gender, race, and education. In so doing, we aim to make comparisons on a more equitable basis, accounting for demographic differences across areas. As long as local amenities stay roughly constant, these adjusted changes are more likely to represent real gains (or losses) in well-being.

Our main focus is on the period from the business cycle peak of 2000 to the business cycle peak of 2015–2019, which we regard as a good measure of long-term CZ trends. Over this period, even after controlling for population composition, there are large variations across CZs in changes in employment rates, real wages, and real earnings. Changes in employment rates and changes in wages are only modestly correlated, so CZs that do well in real wage changes may do poorly in changes in employment rates, and vice versa.

If we focus on annual real earnings—which jointly captures the share of people working, the annual hours they work, and the wages paid per hour, and thus serves as a good summary indicator—we find some expected patterns, including many booms in large, high-tech coastal cities. However, we also find that not all smaller areas have done poorly. Many smaller CZs in fact have had greater success than the coastal high-tech centers that attract frequent media attention. Some of this is due to local price trends, particularly in housing, which can make growth in real wages and real earnings look quite different from the more visible trends in nominal wages and nominal earnings.

The success of CZs also differs widely across demographic groups. A CZ's real earnings growth between 2000 and 2015–2019 for those with less than a bachelor's degree is only moderately correlated with the same growth for those with a bachelor's degree or more. Trends across racial groups are even less correlated. Some areas (e.g., San Francisco) have achieved great success for college-educated workers and white workers while making only minimal progress for non-bachelor's workers and Black workers. Other areas (e.g., Pittsburgh) have achieved great earnings growth for both more- and less-educated workers, as well as for white workers, but still show lagging growth for Black workers.

In explaining trends in economic success, we find some role for industrial mix. A place that specializes in industries doing better nationally, in job growth or wage growth, tends to perform better. But demographics also make a major difference. Places with a higher proportion of Black workers show less success for all workers, and particularly so for workers with less than a bachelor's degree or who are Black. Places with more college-educated workers show greater success for such college-educated workers, but not for other groups. In sum, an area's industries tells only part of its future. And demographics are not destiny, but they do matter greatly.

Yet, most of a local labor market's fortunes cannot be explained by industrial mix or demographics. Much local variation remains, and one can find local labor markets that look similar at the start but exhibit diverse trends. Supplementing the quantitative data with careful case studies of select local labor markets can yield plausible stories, which sometimes aggregate to compelling themes, of why some local areas diverged from expectations.

2. BACKGROUND ON TRENDS FOR DIFFERENT U.S. WORKERS

Since at least the 1970s, earnings inequality across U.S. workers has increased, as has the variance of an individual's earnings over the career (Hoffmann, Lee, and Lemieux 2020). Since 2000, and perhaps earlier, the rising dispersion of earnings has been driven more by top earners pulling away from others, rather than from rising disparities between low earners and the median worker (Autor 2014; Gould 2020).

Much of the increase in earnings inequality over the past 50 years is due to rising labor market returns to education. However, research is less certain whether rising education differentials have continued to play a major role since 2000, with some studies finding support for this trend (Hoffmann, Lee, and Lemieux 2020), while others finding a diminished role more recently (Beaudry, Green, and Sand 2016; Autor 2019; Gould 2020). Many of these studies also find widening earnings gaps *within* education groups.

Black workers have made some labor market progress since the 1960s in closing labor market gaps with white workers, particularly at the 90th percentile of their respective earnings distributions, but this progress has slowed. Since 2000, there has been minimal progress in reducing Black/white earnings differentials at any point of the distribution, and gaps at the median have actually increased (Bayer and Charles 2018). Hispanic workers, however, have made significant progress over this period (Gould 2020).[2]

Additionally, intergenerational upward mobility appears to be much lower for Black workers, especially Black men, than for white workers or Hispanic workers. Some of these deficits may be due to greater Black concentration in poorer neighborhoods, but even for those

[2] More recently, the recovery from the COVID pandemic may have begun to reverse these trends by race, education, and part of the earnings distribution (Autor, Dube, and McGrew 2023), but it is unclear how long this shift will last, and it has been relatively small compared to the decades-long trends that preceded it.

who grew up in the same neighborhood, intergenerational upward mobility is lower for Black men than for white men. This extra racial gap may reflect not only labor market discrimination but other barriers from earlier in life (Chetty et al. 2020).

Earnings inequality has also increased across places. In the past, areas with lower per capita incomes tended to converge towards the U.S. average over time, but this trend has stopped in recent decades (Ganong and Shoag 2017; Austin, Glaeser, and Summers 2018). As employment rates for men aged 25–54 (“prime-age”) have declined nationally, particularly for Black workers (Bayer and Charles 2018), disparity in prime-age employment rates has grown across places (Austin, Glaeser, and Summers 2018), and gaps have become more persistent (Bartik 2020).

The causes of this rising dispersion across groups and across places are not fully understood. Part of the trends are due to rising education wage differentials (Hoffmann, Lee, and Lemieux, 2020; Bayer and Charles 2018). Part may also be due to “institutional” changes in labor markets, such as a declining real value of the minimum wage and declining unionization (DiNardo, Fortin, and Lemieux 1996; Bayer and Charles 2018; Gould 2020). Another possible factor may be the decline in “middle-wage” occupations, particularly in many larger cities. Such middle-wage occupations—often in manufacturing and skilled blue-collar work—pay better than low-wage service occupations but require less education than many high-wage, professional occupations (Autor 2019). Agglomeration economies, or rising productivity when similar workers cluster geographically, may also play a role. Much of recent U.S. economic growth has been concentrated in relatively few large, and often high-tech, coastal cities (Austin, Glaeser, and Summers 2018).

How do we change these trends? Evidence suggests that labor market inequality can be alleviated, at least partly, through faster job growth in more-distressed places (Bartik 2020, 2022a). Not only does faster job growth increase employment *rates* in the long run (Hershbein and Stuart 2023a), it also tends to boost real wages in the short run, and perhaps longer. Furthermore, increased growth in distressed places often leads to faster gains in lower parts of the income distribution and among less-educated groups, although the evidence is more mixed for Black workers (Bartik 1996).

The type of job growth also matters. Middle-wage job growth in a local labor market tends to especially benefit less-educated groups (Bartik 2022b). In contrast, growth in jobs with the highest wages and requiring high levels of education tends to *reduce* effective earnings of less-educated workers, in part because this type of job growth pushes up local prices. Low-wage job growth in a local economy *sometimes* helps less-educated workers, but only if the local labor market is already "tight" (e.g., has a high employment rate), because it puts upward pressure on wages for these workers.

We still need more research to understand additional ways to promote inclusive labor market growth that extends to a wide variety of education and racial groups. However, this research has to begin with *measuring* the diverse labor market trends across areas, which we turn to next.

3. DATA AND METHODOLOGY

Defining Labor Markets

Our primary definition of local labor markets are "commuting zones" (CZs), which were originally developed by economists at the U.S. Department of Agriculture, and since updated by researchers at Pennsylvania State University.[3] Like metropolitan areas and micropolitan areas (Core-Based Statistical Areas, or CBSAs), developed by the Office of Management and Budget and U.S. Census Bureau, CZs cluster counties based on their degree of inter-commuting. Unlike CBSAs, CZs include every county in the United States, not just those around urbanized areas. Even when the two partially overlap, CZs tend to group nearby rural counties more often with a metropolitan or micropolitan area.

Among all 625 U.S. CZs, we focus on the 371 whose year 2000 population exceeded 100,000, for which sample sizes permit more reliable estimates. These CZs comprised 96 percent of total U.S. population.[4] While we exclude the most rural parts of the country, our sample does include many of the relatively rural and smaller areas that are perceived as having fallen behind large coastal cities.

Are commuting zones the "right" definition of local labor markets? Are they better than CBSAs, or the Bureau of Economic Analysis's even larger Economic Areas? To our knowledge, this topic has never been systematically analyzed. We have conducted sensitivity analyses to see how our results differ when defining local labor markets based instead on CBSAs, and we generally find very close agreement in results. However, the greater inclusion of rural areas with CZs does seem an advantage, given current concerns about the economies of rural areas.

[3] The Department of Agriculture constructed CZs based on commuting flows from data in the decennial Censuses, but the relevant questions were last asked in 2000, when the Census Bureau replaced the long form of the Census with the American Community Survey. Researchers at Pennsylvania State University adapted the Agriculture Department's approach based on the latter survey, albeit with a smaller sample size, to cover areas as of 2010 (Fowler and Jensen 2020).

[4] In contrast, if we use the 383 CBSAs that exceed 100,000 in population, we include only 84 percent of the total U.S. population. This illustrates the more expansive geographic borders of CZs.

Defining Labor Market Success

What is local labor market success? Three possible elements of labor market "success" are: 1) the employment to population ratio, or employment rate; 2) the real hourly wage; and 3) real annual earnings. For a person who might be on the margin between employment and nonemployment, the ability to readily find and keep a job, as reflected in the employment rate, might be the most important. For someone employed full time throughout the year, the real hourly wage might best represent the strength of local labor market opportunities. Finally, real annual earnings depend on both the employment rate and the real hourly wage, as well as hours worked per week and the number of weeks worked during the year.[5] Real annual earnings is thus in some sense an "average" bottom line, although employment rates and real hourly wage rates clearly matter, too.

Our analysis also seeks to control for local price variations. Local price levels vary primarily because of different housing prices. Higher housing prices tend to put upward pressure on wages and thus also on the costs of goods and services produced and consumed locally. High wages, even when accounting for overall inflation, don't go as far in high-cost-of-living areas, and even low wages may provide more purchasing power when housing is relatively cheap. Adjusting for these local price differences makes intuitive sense for overall success measures. As we explain below, this is especially true when considering changes over time.

Another difference that complicates simple comparisons of published estimates is the variation across areas in population age, education, race, and gender, as labor market measures vary widely across these groups. We want to compare apples with apples: How does a person

[5] We thus include individuals with zero annual earnings to capture the variation in employment intensity as well as hourly wages. Our measure of the real hourly wage, however, is based on individuals who report minimal work attachment (at least 14 weeks worked in the past year or 12 months, as well as 10 hours worked per week), as hourly wages need to be constructed from the data and are not directly reported.

with given demographic characteristics fare in a specific local labor market compared to the nation as a whole? We thus adjust for these demographics when measuring labor market outcomes both for the overall population of an area and for particular groups in that area. For example, in comparing labor market outcomes for Black workers, we want to control for the education, age, and gender of Black workers in that local area relative to the same characteristics for Black workers in other areas or the nation as a whole.

Our primary focus is not necessarily comparing the *levels* of labor market outcomes across different CZs—what researchers call the cross-section—but rather the *change over time* in labor market outcomes for each CZ. If a local labor market offers higher or lower real earnings, much of this differential may be due to differences in local amenities. An area with a more pleasant overall climate that is otherwise identical to another area would generally be expected to have lower real earnings, on average, because residents are willing to give up some of their earnings to enjoy, or implicitly pay for, the nice climate.[6] On the other hand, *changes over time* in local labor market outcomes, particularly if they are large, are much less likely to be offset by amenity changes. Many amenities barely change over time (e.g., climate, proximity to oceans or mountains), although some can and do over a decade or two (e.g., availability of ethnic cuisine, presence of bike trails). Still, changes in economic measures over time are less likely to be driven by amenities, and we therefore view large changes in labor market outcomes as representing real changes in worker well-being.[7]

[6] As shown in Bartik and Smith (1987), amenities are more likely to be capitalized in local prices than into local wages, largely because labor costs are more important in determining business location decisions than land costs, which limits how much amenities valued by households can be reflected in wages. This assumes that amenities are primarily directly valued by households, rather than firms.

[7] Diamond (2016) notes that local amenities do change endogenously in response to migration. Our point is that large changes in measured outcomes are unlikely to be fully accounted for by amenity changes.

In addition to measures for the overall working-age population of a CZ, we also examine measures for different demographic groups to determine the extent to which improvement (or decline) is “inclusive” of all groups. Although we acknowledge that the value of amenities may also change somewhat differently across groups in the same CZ, there is considerable correlation. Thus, comparing labor market outcomes across groups likely reflects real differences in groups’ changing labor market fortunes in the CZ.

Data Sources and Sample Construction

To construct our measures, we use data from the 2000 Population Census and American Community Surveys (ACS) from years 2005–2007, and from 2015–2019 (Ruggles et al. 2023). The Census and ACS provide large sample sizes that allow estimates even for most CZs. The 2000 Census is approximately a 5 percent sample of the U.S. population, and the annual ACS is about a 1 percent sample, so the latter two periods are approximately a 3 percent and 5 percent sample, respectively.

The particular years of 2000, 2005–2007, and 2015–2019 are chosen because they are close to business cycle peaks. We are trying to capture long-term trends in a CZ’s labor market outcomes, and focusing on CZ performance near a business cycle peak makes more sense than focusing on performance during the depths of a recession.[8] Our greatest focus is on changes between 2000 and 2015–2019. This longer-term trend perspective sidesteps possible problems relating to the housing bubble prior to the Great Recession, which might distort comparisons using the 2005–2007 period. Similarly, we do not extend the window past 2019 to avoid incorporating effects of the COVID pandemic.

[8] This also explains why the 2005–2007 sample is based on only three years (and hence a 3 percent sample), unlike the other two time periods. Extending the sample into 2008 and 2009 would incorporate the Great Recession.

We limit our analysis to CZs exceeding 100,000 in population (as of 2000). We make this choice for a few reasons. First, as mentioned earlier, small areas may have too few people in the data to produce reliable statistics for certain demographic groups, even with the size of the Census/ACS.

Second, the threshold increases the accuracy of the match between Census/ACS data and CZs. The smallest geographies identified in the Census/ACS microdata files are Public Use Microdata Areas, or PUMAs. These are areas of at least 100,000 people and can be entirely nested within populous counties or span several rural counties. PUMAs can thus be probabilistically matched to counties and CZs. From published estimates, we know the fraction of the population from a particular PUMA that resides in a particular county (and thus in a particular CZ). For CZs with fewer than 100,000 people, the match is likely to involve taking a larger PUMA and apportioning its labor market outcomes to several smaller CZs. This vastly increases the measurement error in ascertaining labor market outcomes in a CZ. In contrast, if the CZ has more than 100,000 people, particularly if it has far more, then PUMAs will likely have their entire population assigned to the CZ, and we can be more confident that the measured labor market outcomes actually correspond uniquely to the correct CZ.[9]

Third, while the size threshold of 100,000 population includes 371 of the 625 CZs, these 371 areas account for the vast majority—96 percent—of the U.S. population.

Adjusting for Prices and Demographics

To adjust for local prices, we first measure relative local housing prices as captured by monthly rents in the Census/ACS. We assume differences in overall local prices are half the

[9] The same issues arise when using CBSAs instead of CZs. Our sensitivity analyses thus include almost every *metropolitan* CBSA—areas with an urban core of at least 50,000 people—but exclude most *micropolitan* CBSAs—areas with urbanized cores of at least 10,000 but fewer than 50,000 people.

housing price differentials across areas—this fractional adjustment accounts for housing's overall share in budgets as well as the indirect effects on the prices of goods and services mentioned above. The exact calculations for these adjustments are in Appendix A, including an explanation of why we use a one-half weight on local housing price differentials in calculating local prices.

We control for detailed demographics within our overall sample of working-age adults aged 25–64. The lower end of the age range is chosen so that we can more accurately measure education for all individuals. The upper end is set to focus on ages prior to traditional retirement age.

We divide our sample into 160 cells. These cells are defined as the intersection of 2 gender categories, 4 race/ethnicity categories, 4 age categories, and 5 education categories. The four race categories are: White non-Hispanic, Black non-Hispanic, Hispanic, and others.[10] The four age categories are 25–34, 35–44, 45–54, and 55–64. The five education categories are: less than a high school diploma, high school graduate but no higher degree, associate degree, bachelor's degree, and graduate degree.

For each of these 160 cells, in each of the three time periods, and in each CZ as well as the nation as a whole, we calculate the average employment rate, the median hourly real wage, and median real annual earnings.[11] We apply person-level sample weights from the Census and ACS, which translate the number of individuals in the dataset to the populations they are meant to represent, accounting for sampling and response rates.

[10] Ideally, we would have separate categories for Asian Americans, Pacific Islanders, and Native Americans, but sample sizes for these groups were too small for this approach to be feasible.
[11] Details of these calculations are in Appendix A.

We choose to focus on the medians of wages and earnings because each of these measures is highly skewed and can include some observations with extreme values, possibly making the mean (or average) less representative of the typical person, especially in smaller cells.[12]

For each time period, we compare the employment rate, the median hourly wage, and median earnings in the CZ to that of the nation. To ensure an apples-to-apples comparison, we apply the same population weights across the 160 demographic cells in the CZ to the corresponding 160 demographic cells at the national level, thus equilibrating demographic composition between the two geographies. The ratio of the two averages—the 160 cells of the CZ to the 160 cells of the nation, applying the same proportional weights to both sets of cells—is then our measure of relative employment rates, median real wages, and median real earnings.

To be more specific, we calculate:

$$(1) \qquad \frac{Y_t^{CZ,cz}}{Y_t^{US,cz}} = \frac{\sum_j S_{jt}^{cz} * Y_{jt}^{cz}}{\sum_j S_{jt}^{cz} * Y_{jt}^{us}}$$

Here, S_{jt}^{cz} is the share of persons in the CZ who are in demographic cell (or subgroup) *j* at time *t*. Y_{jt}^{cz} is the pooled labor market outcome (mean employment rate, median real wage, or median real earnings) in the CZ for subgroup *j* at time *t*. Y_{jt}^{us} is the pooled labor market outcome in the United States at time *t* for subgroup *j*. The summation aggregates over all 160 demographic cells.[13] In the numerator on the left-hand side of the equation, $Y_t^{CZ,cz}$ is the average over all 160 demographic cells of a labor market outcome for the CZ in time period *t* (which equals the

[12] We do, however, examine real mean earnings and real mean hourly wages in sensitivity analyses.
[13] This holds when calculating ratios for the overall population aged 25–64. When calculating ratios for specific groups (e.g., Blacks or those with less than a bachelor's degree), the summation is over the cells belonging to that group.

overall average of the labor market in the CZ in that period). In the denominator, $Y_t^{US,cz}$ is the average labor market outcome that would occur for the CZ if each demographic cell's outcome matched the U.S. average, but the mix across cells stayed the same. Intuitively, the ratio on the left-hand side captures an average labor market outcome for a CZ relative to what this outcome would be if every constituent demographic group performed at its national average.

We can multiply the numerator by Y_{jt}^{us}/Y_{jt}^{us} to get the following reformulation of Equation (1):

$$(2) \qquad \frac{Y_t^{CZ,cz}}{Y_t^{US,cz}} = \frac{\sum_j S_{jt}^{cz} * Y_{jt}^{us} * \frac{Y_{jt}^{cz}}{Y_{jt}^{us}}}{\sum_j S_{jt}^{cz} * Y_{jt}^{us}}$$

This provides a reinterpretation of the index as a weighted average of the ratio of labor market outcomes between the CZ and nation, $\frac{Y_{jt}^{cz}}{Y_{jt}^{us}}$, for each of the 160 cells *j*, where the weights are the product of the cell's sample share in the area (S_{jt}^{cz}) and the national measure for the cell (Y_{jt}^{us}).

A similar procedure can be applied for any subgroup. For Black workers, for example, there are 40 cells (2 genders by 4 age groups by 5 education groups). These 40 cells in each CZ are aggregated using their proportional weights, and national medians (or means) for Black workers are similarly aggregated using the *same* local weights, separately for each CZ. The ratio of these two weighted calculations—for the CZ and the nation, both using the CZ's proportional weights—yields our measure of overall Black employment rates (or median hourly wage, or median annual earnings). Because the same demographic weights are used for both the CZ and the nation, the procedure explicitly controls for demographic differences between the geographies. The exercise asks how different the outcome is for the CZ relative to the nation, if the two were to have identical shares of people in each detailed cell.

Our choice of using local weights results in different weighting schemes for each CZ and time period. An alternative would be to use the same weights for all calculations—for example, by using national shares from a fixed time period for each of the 160 groups. In practice, however, this approach is infeasible because many CZs have no sample observations for one or more of the 160 demographic cells. With zero observations, no average labor market outcome can be calculated for that cell in that CZ, and we thus cannot calculate any group averages that put any non-zero weight on that missing cell.

The choice of weights is an index number problem. In comparing labor market outcomes across a group of workers with different subgroup composition in different places or times, we can hold constant the composition of each group in various ways, but this choice should not much affect the relative indices for the outcomes.[14] We prefer our chosen weighting scheme because of its feasibility and meaningful interpretation: How would a particular group of people in a CZ fare if all its constituent subgroups matched their national averages?

Finally, we examine changes over time by taking differences in the natural logarithm of the indices, whether for employment rates, median real hourly wages, or median real annual earnings. The same interpretation holds, but dynamically in this case: How would the CZ group fare if its constituent subgroups had their outcomes *change* at the same rate as their national averages.

[14] An analogous comparison is calculating average prices across a bundle of goods with different subgroup composition sold in different times—that is, an inflation index.

4. RESULTS: OVERALL AND FOR PARTICULAR GROUPS

We first consider some overall average results, across everyone aged 25–64, in levels and trends both for the nation and for particular CZs. We then consider CZ trends for different education and racial/ethnic groups.

Overall Averages and Trends

Table 1 reports national levels and time trends in average employment rates, median real hourly wages, and median real annual earnings for working-age adults (aged 25–64) in each time period. We present both "unadjusted" numbers reflecting the demographic mix in each time period as well as "adjusted" numbers that hold the composition of the 160 subgroups fixed at their 2015–2019 shares. Differences in these latter numbers are thus net of demographic changes.

Table 1 National Trends in Employment Rates, Real Wages, and Real Earnings for 25–64-Year-Olds, Unadjusted vs. Adjusted for Demographic Changes

	Employment rate		*Real median wage*		*Real annual earnings*	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
2000	78.0%	77.5%	$23.02	$24.22	$32,249	$32,838
2005–2007	76.0%	75.9%	$23.57	$24.48	$32,232	$32,793
2015–2019	74.6%	74.6%	$24.34	$24.34	$33,274	$33,274
% growth:						
2000 to 2005–2007	−2.5%	−2.1%	2.4%	1.1%	−0.1%	−0.1%
2005–2007 to 2015–2019	−1.8%	−1.7%	3.3%	−0.5%	3.2%	1.5%
2000 to 2015–2019	−4.3%	−3.7%	5.8%	0.5%	3.2%	1.3%

NOTE: "Unadjusted" numbers reflect national aggregates calculated in each time period, while "adjusted" numbers hold each of 160 demographic cell weights at their shares from 2015–2019, with values aggregated across cells using these share weights. Adjusted numbers thus hold demographic composition fixed across time. For both sets of numbers, we have further modified employment rates to correct for differences between Census measures of this outcome and official measures as captured by the Bureau of Labor Statistics (BLS). (Prior to 2008, Population Census and ACS undercounted employment relative to BLS figures; our modification process ratio-adjusts the Census/ACS estimates to make them comparable to the BLS numbers and thus comparable over time.)

SOURCE: Authors' calculations as described in text.

Looking first at the unadjusted numbers, employment rates fell by 3.4 percentage points (4.3 percent) between 2000 and 2015–2019, while median real annual earnings and median real hourly wages both rose, by 3.2 percent and 5.8 percent, respectively. These trends reflect, in part, aging of the population—which tends to reduce the employment rate—and increasing educational attainment—which tends to increase wages. Adjusting for changes to demographic composition across all 160 cells slightly mitigates the decline in the employment rate, to a loss of 2.9 percentage points (3.7 percent), but it also shrinks the gains in earnings and wages, to 1.3 percent and 0.5 percent, respectively. These patterns indicate a somewhat lackluster trend in labor market outcomes for the United States as a whole during the first two decades of the 21st century. Most gains in earnings and wages are due to changing demographic composition rather than "organic" growth, and employment rates even of the working-age population have ebbed.

Our focus, however, is on local labor markets, and some of these will have exceeded national growth, while others will have lagged even further. As mentioned, we focus on *changes* in CZ labor market outcomes, because *levels* of CZ outcomes may reflect persistent local amenities (or disamenities) that policymakers cannot readily change. Still, it is illustrative to first examine these outcome levels (or ratio indices thereof, as described above) across CZs. Table 2 presents some descriptive statistics of the labor market outcomes for the 371 CZs in our sample over the 2015–2019 period, along with various correlations of these overall indices for each CZ.

The first row of Table 2 shows the mean of each outcome index across the 371 (equally weighted) CZs. Without any adjustment for price levels or demographic composition, each mean is below 1, indicating that the majority of CZs (particularly smaller ones) fare worse than the United States as a whole along the three labor market dimensions. After adjusting for local price levels and demographics, the index means are much closer to 1, which suggests these two factors play a large role in explaining geographic variation in the *levels* of the outcomes.[15]

[15] In particular, price adjustments tend to increase relative real wages and real earnings in smaller CZs.

Indeed, adjustment for demographics reduces the standard deviation across the 371 CZs of employment rates, real median hourly wages, and real median annual earnings. However, considerable variation still remains, with standard deviations of almost 7 percent for both the employment rate and real wage indices, and over 17 percent for the real earnings index.

Table 2 Selected CZ-level Statistics for Indices of Employment Rates, Real Median Wages, Real Median Annual Earnings, for 2015–2019, Raw and Adjusted for Demographic Composition

	Employment rate		*Real median wage*		*Real annual earnings*	
	Unadjust.	Adjusted	Unadjust.	Adjusted	Unadjust.	Adjusted
Mean index (2015–2019)	0.960	0.975	0.877	1.029	0.825	0.984
Standard deviation (2015–2019)	0.085	0.067	0.131	0.065	0.252	0.172
<u>*Correlations of Indices*</u>						
Adjusted with unadjusted		0.974		0.733		0.132
Adjusted w/ partial adjustment only for local prices				0.884		0.642
Adjusted w/ partial adjustment only for demographics				0.862		0.291
Medians with means				0.919		0.942
2015–2019 with 2000		0.897		0.787		0.805
2015–2019 with 2005–2007		0.922		0.874		0.829
2005–2007 with 2000		0.919		0.909		0.880
Emp. rate with median wage				0.016		
Emp. rate with earnings						0.802
Median wage with earnings						0.502

NOTE: Statistics refer to indices of employment rates, median real wage rates, and median real earnings for 371 commuting zones (CZs) as described in the text, with equal weight for each CZ. "Unadjusted" indices reflect each CZ's own price level and demographic mix relative to the United States while "adjusted" numbers effectively hold these fixed across CZs; see Section 3, subsection "Adjusting for Prices and Demographics" in text.

SOURCE: Authors' calculations.

The second panel of Table 2 reveals how the different measures are correlated with each other, as well as to alternative formulations. The first row of this panel shows that for employment rates the adjusted and unadjusted index are very highly correlated, suggesting that demographic composition is not central in explaining geographic variation in the likelihood of employment. On the other hand, this correlation is lower for real median hourly wages and much lower for real median annual earnings, reflecting the role of relative price levels. The following two rows thus highlight the role of each adjustment factor by adjusting for only one at a time. Correlations between the fully adjusted and "partially adjusted" indices suggest that local price adjustment and demographic composition adjustment both matter, but that price adjustment is more important for the earnings index.

Although we prefer to focus on median wages and median earnings to minimize the influence of outliers in the microdata, for comparison we also have calculated CZ indices based on means for these outcomes. Table 2 shows that indices based on means are highly correlated (over 0.9) with those based on medians.

The index levels for each outcome are also highly correlated across the three time periods, particularly for employment rates. This high persistence suggests that much of the variation across places in the levels of the labor market indicators is due to relatively fixed features of the areas (e.g., amenities). However, to the extent these (unobserved) features affect individual well-being, level differences in the labor market indicators are insufficient measures when comparing the success of places.

Finally, the last rows of Table 2 compare the adjusted indices across labor market indicators. The employment rate index is essentially uncorrelated with the real median hourly wage index across CZs. These two indices appear to represent quite different aspects of a local labor market's performance. On the other hand, a CZ's real earnings index has greater correlation with its employment rate index than with its real hourly wage index. The employment rate index may not capture just whether someone works at all but also their usual weekly hours and annual weeks worked, which both affect annual real earnings, perhaps more even than the hourly wage.

In Table 3, we turn to considering *changes* in these indices from 2000 to 2015–2019. Changes in the indices more likely reflect labor market shifts that affect an individual's well-being. The numbers in the table reflect subtracting the natural logarithm of the 2000 index from the natural logarithm of the 2015–2019 index, with this log difference expressed in percentage terms.

Table 3 Selected CZ-level Statistics for *Changes* in Indices of Employment Rates, Real Median Wages, Real Median Annual Earnings, 2000 to 2015–2019

	Employment rate		*Real median wage*		*Real annual earnings*	
	Unadjust.	Adjusted	Unadjust.	Adjusted	Unadjust.	Adjusted
Mean Δ index (2000 to 2015–2019)	−2.8%	−1.5%	−1.0%	2.5%	−6.3%	−1.0%
Std. deviation Δ (2000 to 2015–2019)	4.0%	3.1%	5.6%	4.1%	14.5%	11.4%
<u>*Correlations of Indices*</u>						
Adjusted Δ with Unadjusted Δ		0.778		0.597		0.894
Adjusted Δ w/ partial adjustment only for local prices Δ				0.797		0.935
Adjusted Δ w/ partial adjustment only for demographics Δ				0.745		0.960
ΔMedians with ΔMeans				0.911		0.861
Δ(2015–2019, 2000) with Δ(2005–2007, 2000)		0.449		0.505		0.584
Δ(2015–2019, 2000) with Δ(2015–2019, 2005–2007)		0.722		0.668		0.850
Δ(2015–2019, 2005–2007) with Δ(2005–2007, 2000)		−0.295		−0.304		0.068
Emp. rate Δ with median wage Δ				0.146		
Emp. rate Δ with earnings Δ						0.679
Median wage Δ with earnings Δ						0.535

NOTE: Unless otherwise specified, statistics refer to *changes* in indices of employment rates, median real wage rates, and median real earnings between 2000 and 2015–2019 for 371 commuting zones (CZs) as described in the text, with equal weight for each CZ. See note to Table 2.

SOURCE: Authors' calculations.

The first row of the table shows that, consistent with Table 1, the majority of areas witnessed deterioration in their labor market indicators over the first two decades of the century. Adjusting for demographics and price levels across areas and over time, however, ameliorates much of the decline and even shows slight average gains for median hourly wages.

Moreover, considering *changes* leads to less variation across areas than considering *levels*. Across CZs, the standard deviation for the (adjusted) employment rate *change* between 2000 and 2015–2019 is 3.1 percent; the standard deviation for the employment rate *level* in 2015–2019 (Table 2) is 6.7 percent. Similarly, the standard deviation for the hourly wage index change is 4.1 percent, compared to 6.5 percent for the level index, and the standard deviation for the annual earnings index change is 11.4 percent, relative to 17.2 percent for the level index. Nonetheless, these standard deviations in changes are still quite large: a two-standard-deviation difference in the change in real earnings is nearly 23 percent, a magnitude on par with the growth in real median household income between the mid-1980s and today (Shrider et al. 2021).

Comparing the correlations of the adjusted and unadjusted index *changes*, we find that the correlations are lower for employment and median wages than they were for *levels* (Table 2); this suggests that demographics and price levels may affect differential growth across CZs in these outcomes. In contrast, the correlation between adjusted and unadjusted index changes in annual earnings is higher than it was for levels, suggesting that other factors besides demographics and initial price levels drove cross-area variation in earnings growth.

As with the levels analysis, the changes analysis shows a high correlation across CZs when using medians or means for the real hourly wage and real annual earnings variables. Outliers in individual reports for these measures do not change the big picture (although they may still affect measures for specific CZs).

Turning to the next three rows of Table 3, we examine the correlations of index changes across time periods. As expected, we find that changes over the entire 2000 to 2015–2019 period are positively correlated with changes during each of the business cycles that comprise this period (2000 to 2005–2007 and 2005–2007 to 2015–2019). However, changes during the later business cycle are not positively correlated with changes in the earlier business cycle; if anything, they are negatively correlated. This lack of positive correlation across business cycles may reflect that different economic forces influenced relative CZ labor market success during the housing bubble business cycle (2000 to 2005–2007) than during the post–Great Recession business cycle (2005–2007 to 2015–2019).

As was true with the levels analysis, the last three rows show that changes in real earnings over time are somewhat more related to changes in employment rates than to changes in real hourly wages. Furthermore, changes in employment rates and changes in wages are only weakly correlated. CZs that experience rising employment rates may not experience rising real hourly wages, and vice versa.

Averages and Trends for Select CZs

But what does labor market success look like for individual CZs? Examining all three labor market outcome variables for all 371 CZs is challenging, especially in a single report.[16] In Table 4, we focus on CZs ranking near the top or bottom based on changes in the annual earnings index between 2000 and 2015–2019. We consider the top 5 and bottom 5 CZs in each of three size classes.

[16] We will make available data on all CZs (and CBSAs) in spreadsheet form, and we are also creating a web interactive that will allow users to examine data from selected areas.

Table 4 Top 5 and Bottom 5 CZs in Earnings Index Change between 2000 and 2015–2019, by Size Class

		Largest city	2000 pop. (millions)	Emp. rate change	Hourly wage change	Ann. earnings change
Panel A: CZs ≥1M in 2000 pop						
Top 5	Allegheny, PA	Pittsburgh	2.603	3.8%	0.9%	11.2%
	Hillsborough, NH	Manchester	1.193	1.2%	4.7%	9.0%
	King, WA	Seattle	3.942	0.8%	5.8%	8.8%
	Alameda, CA	San Francisco	5.101	1.6%	5.2%	8.6%
	Oklahoma, OK	Oklahoma City	1.107	−0.2%	7.9%	5.5%
Bottom 5	Hidalgo, TX	McAllen	1.070	1.2%	0.3%	−8.7%
	Orange, FL	Orlando	2.074	−1.8%	−0.3%	−9.4%
	Wayne, MI	Detroit	5.077	−0.4%	−8.0%	−10.8%
	Kern, CA	Bakersfield	1.159	1.0%	3.5%	−11.4%
	Miami-Dade, FL	Miami	3.956	2.5%	−8.9%	−12.6%
Panel B: CZ 500K–1M in 2000 pop						
Top 5	Cambria, PA	Johnstown	0.501	2.9%	3.8%	11.4%
	Stark, OH	Canton	0.701	1.0%	2.1%	9.6%
	Santa Barbara, CA	Santa Maria	0.646	4.4%	1.9%	9.1%
	Dane, WI	Madison	0.683	0.8%	5.9%	7.8%
	Polk, IA	Des Moines	0.507	0.2%	8.3%	7.7%
Bottom 5	Brevard, FL	Palm Bay	0.589	−3.8%	0.4%	−15.2%
	Muscogee, GA	Columbus	0.545	−6.2%	−2.4%	−16.4%
	Genesee, MI	Flint	0.956	−3.3%	−7.1%	−16.9%
	Horry, SC	Myrtle Beach	0.620	−5.6%	−3.1%	−20.4%
	Polk, FL	Lakeland	0.598	−4.2%	−3.1%	−25.3%
Panel C: CZ 100–500K in 2000 pop						
Top 5	Burleigh, ND	Bismarck	0.126	6.6%	15.2%	38.1%
	Twin Falls, ID	Twin Falls	0.120	1.2%	6.3%	29.2%
	Chelan, WA	Wenatchee	0.146	3.4%	10.8%	27.5%
	Midland, TX	Midland	0.159	3.6%	9.3%	27.2%
	Otter Tail, MN	Fergus Falls	0.156	4.0%	10.0%	26.5%
Bottom 5	Dallas, AL	Selma	0.138	−11.4%	−0.5%	−32.5%
	Washington, MS	Greenville	0.158	−14.2%	−4.1%	−32.6%
	Halifax, VA	South Boston	0.173	−5.0%	−3.4%	−34.6%
	Laurens, GA	Dublin	0.105	−9.1%	−2.7%	−40.5%
	Navajo, AZ	Show Low	0.267	−8.7%	−1.1%	−64.2%

NOTE: We name CZs by their most populous county but also provide the largest city for context. Rate changes are based on adjusted indices. All changes are percentage changes, measured as the change in the natural logarithm of these adjusted indices.

Among the largest CZs, the booming areas tend to be high-tech centers, such as Pittsburgh, Seattle, San Francisco, and Boston-adjacent Manchester. But among CZs in other size classes, booming areas tend to be more diverse, with some economies dependent on government (state capitals), natural resources, tourism, or other sectors. Depressed areas, in contrast, include both Rustbelt cities, such as Detroit and Flint, and several—often smaller—southern communities.

Among both booming and distressed communities, the changes in the earnings index sometimes correlate more closely with changes in the employment rate index changes and other times more so with changes in the hourly wage index. For example, Pittsburgh's success in boosting annual earnings came with significant increases in employment rates, but not in hourly wages. In contrast, the earnings improvements in Seattle and Oklahoma City came about through gains in hourly wages, not employment rates.

Results by Education Groups

We next analyze trends for different education groups: those with less than a bachelor's degree (sub-BA), and those with at least a bachelor's degree (BA+).[17] In each case, the indices we create control for both local prices and the demographic mix *within* these two broad educational categories.

We focus on the longer horizon change from 2000 to 2015–2019. Because almost two-thirds (64.7 percent) of the sample (and the population) have less than a bachelor's degree, the change in the sub-BA earnings index is highly correlated (0.961) with the change in the overall

[17] In terms of the 160 demographic cells, the sub-BA group has 3 education categories (high school dropout, high school graduate but no higher degree, associate degree) by 2 genders by 4 age groups by 4 race groups, or 96 cells. The BA+ group has 2 education categories (BA only, higher degree) by 2 genders by 4 age groups by 4 race groups, or 64 cells.

earnings index. This correlation is slightly weaker, although still robust (0.732), between the overall index and that for the BA+ group. However, the changes in the sub-BA and BA+ indices are less correlated with each other, at 0.568. CZs that are good at advancing the earnings of those with bachelor's or graduate degrees also tend to show earnings growth for those without a bachelor's, but not always so.

There is also much greater variation across CZs in the change in the sub-BA earnings index than in the BA+ index, with the former having a standard deviation (17.2 percent) more than twice the latter (8.4 percent). Put differently, the economic fortunes of individuals with less than a bachelor's degree are more tightly linked to the CZ in which they reside.

In Tables 5 and 6, we examine top-ranked and bottom-ranked CZs according to earnings index changes over the entire two-decade horizon. Table 5 ranks CZs by the change in the earnings index for the sub-BA group while Table 6 ranks index changes for the BA+ group. For each table, however, we report changes in the earnings index for *both* education groups as well as for residents overall, allowing us to see whether the CZs that benefit one education group also benefit the other.

As Tables 5 and 6 show, areas that demonstrate large earnings gains for individuals with a bachelor's degree do not necessarily do the same for individuals without a bachelor's degree, and vice versa. For example, San Francisco and Phoenix have healthy gains for the BA+ group, but little gains for the sub-BA group. Pittsburgh, Salt Lake City, Buffalo, and Albany, on the other hand, all show healthy trends in earnings gains for the sub-BA group, but little gains for the BA+ group. In contrast, Manchester, Minneapolis, and Seattle show strong earnings gains for both education groups.

Table 5 Top 5 and Bottom 5 CZs Earnings Index Changes between 2000 and 2015–2019, by Size Class, Ranked by Sub-BA Earnings Index Changes

		Largest city	2000 pop (millions)	Sub-BA earnings change	BA+ earnings change	Overall earnings change
Panel A: CZs ≥1M in 2000 pop						
Top 5	Allegheny, PA	Pittsburgh	2.603	21.2%	1.4%	11.2%
	Hillsborough, NH	Manchester	1.193	13.3%	8.5%	9.0%
	Salt Lake, UT	Salt Lake City	1.826	13.3%	1.6%	5.0%
	Erie, NY	Buffalo	1.408	10.9%	0.0%	5.0%
	Albany, NY	Albany	1.171	9.8%	1.9%	5.2%
Bottom 5	Orange, FL	Orlando	2.074	−11.9%	−6.8%	−9.4%
	Los Angeles, CA	Los Angeles	16.373	−11.9%	−7.6%	−8.5%
	Sacramento, CA	Sacramento	1.780	−12.4%	−1.4%	−4.9%
	Wayne, MI	Detroit	5.077	−14.7%	−8.3%	−10.8%
	Kern, CA	Bakersfield	1.159	−21.3%	−1.2%	−11.4%
Panel B: CZ 500K–1M in 2000 pop						
Top 5	Cambria, PA	Johnstown	0.501	19.7%	−4.6%	11.4%
	Santa Barbara, CA	Santa Maria	0.646	15.8%	5.1%	9.1%
	Douglas, NE	Omaha	0.803	14.9%	4.7%	7.3%
	Outagamie, WI	Appleton	0.550	14.0%	4.4%	7.4%
	Stark, OH	Canton	0.701	13.4%	6.5%	9.6%
Bottom 5	Saginaw, MI	Saginaw	0.541	−19.6%	−2.2%	−9.5%
	Sullivan, TN	Kingsport	0.543	−22.1%	−4.3%	−12.1%
	Genesee, MI	Flint	0.956	−24.6%	−9.6%	−16.9%
	Brevard, FL	Palm Bay	0.589	−25.3%	−9.1%	−15.2%
	Polk, FL	Lakeland	0.598	−29.7%	−18.0%	−25.3%
Panel C: CZ 100–500K in 2000 pop						
Top 5	Burleigh, ND	Bismarck	0.126	50.3%	26.6%	38.1%
	Midland, TX	Midland	0.159	45.6%	2.9%	27.2%
	Twin Falls, ID	Twin Falls	0.120	36.4%	19.0%	29.2%
	Otter Tail, MN	Fergus Falls	0.156	33.6%	16.0%	26.5%
	Garfield, CO	Glenwood Springs	0.137	32.2%	16.0%	19.7%
Bottom 5	Dallas, AL	Selma	0.138	−47.3%	−13.2%	−32.5%
	Angelina, TX	Lufkin	0.238	−50.0%	−7.5%	−31.6%
	Laurens, GA	Dublin	0.105	−58.2%	−18.6%	−40.5%
	Washington, MS	Greenville	0.158	−61.0%	−8.5%	−32.6%
	Navajo, AZ	Show Low	0.267	−115.1%	−14.1%	−64.2%

NOTE: See note to Table 4. The greater than 100% decline for sub-BA earnings for Navajo, AZ is a consequence of our log approximation approach, which is less accurate for very large changes; the true decline is 71.4%.

Table 6 Top 5 and Bottom 5 CZs Earnings Index Changes between 2000 and 2015–2019, by Size Class, Ranked by BA+ Earnings Index Changes

		Largest city	2000 pop (millions)	Sub-BA earnings change	BA earnings change	Overall earnings change
Panel A: CZs ≥1M in 2000 pop						
Top 5	King, WA	Seattle	3.942	8.1%	12.0%	8.8%
	Alameda, CA	San Francisco	5.101	2.4%	11.8%	8.6%
	Hillsborough, NH	Manchester	1.193	13.3%	8.5%	9.0%
	Maricopa, AZ	Phoenix	3.470	−0.1%	7.8%	3.3%
	Hennepin, MN	Minneapolis	2.946	8.8%	7.7%	5.4%
Bottom 5	Palm Beach, FL	West Palm Beach	1.533	−3.9%	−7.8%	−7.1%
	Wayne, MI	Detroit	5.077	−14.7%	−8.3%	−10.8%
	Miami-Dade, FL	Miami	3.956	−11.8%	−10.9%	−12.6%
	Honolulu, HI	Honolulu	1.063	4.6%	−11.3%	−6.3%
	Hidalgo, TX	McAllen	1.070	−7.5%	−16.8%	−8.7%
Panel B: CZ 500K–1M in 2000 pop						
Top 5	Polk, IA	Des Moines	0.507	5.4%	13.0%	7.7%
	Dane, WI	Madison	0.683	12.8%	10.6%	7.8%
	Bernalillo, NM	Albuquerque	0.748	−6.4%	9.6%	2.4%
	Cumberland, ME	Portland	0.657	7.0%	7.7%	6.5%
	Stark, OH	Canton	0.701	13.4%	6.5%	9.6%
Bottom 5	Genesee, MI	Flint	0.956	−24.6%	−9.6%	−16.9%
	Greenville, SC	Greenville	0.894	−5.5%	−9.6%	−9.3%
	Muscogee, GA	Columbus	0.545	−19.0%	−13.1%	−16.4%
	Polk, FL	Lakeland	0.598	−29.7%	−18.0%	−25.3%
	Horry, SC	Myrtle Beach	0.620	−19.6%	−22.0%	−20.4%
Panel C: CZ 100–500K in 2000 pop						
Top 5	Burleigh, ND	Bismarck	0.126	50.3%	26.6%	38.1%
	Chelan, WA	Wenatchee	0.146	29.7%	26.1%	27.5%
	Gallatin, MT	Bozeman	0.164	24.2%	24.3%	22.2%
	Mohave, AZ	Lake Havasu City	0.175	−13.9%	20.8%	−2.1%
	Flathead, MT	Kalispell	0.111	21.0%	20.7%	19.3%
Bottom 5	Laurel, KY	London	0.145	−13.6%	−19.0%	−10.8%
	Pulaski, KY	Somerset	0.124	−10.4%	−21.6%	−11.5%
	Harlan, KY	Harlan	0.118	−22.9%	−27.6%	−15.2%
	Pike, KY	Pikeville	0.242	−37.3%	−29.5%	−25.7%
	Raleigh, WV	Beckley	0.165	−10.3%	−33.2%	−14.2%

NOTE: See note to Table 4.

CZs that lost earnings were more likely to show losses for both education groups, especially among the smaller areas. But there are notable exceptions. Sacramento and Bakersfield had double-digit percentage losses in sub-BA earnings while their BA+ earnings dipped only slightly. Honolulu experienced the reverse, with earnings index losses of over 11 percent for BA+ residents, even as its sub-BA earnings index grew by nearly 5 percent**.**

Results by Racial and Ethnic Groups

Motivated by concerns of equity in labor market opportunities, we now turn to considering labor market success across CZs for different racial and ethnic groups: white non-Hispanic workers, Black non-Hispanic workers, and Hispanic workers. Again, our constructed labor market indices for each of these groups hold constant the composition across 40 demographic cells *within* the groups (2 genders × 4 age groups × 5 education groups).

A complication is that some parts of the country have few people of color, making it difficult to construct labor market measures for these areas. To minimize problems due to small sample size, we restrict attention to CZs with at least 100 underlying observations (in the ACS microdata) contributing to the construction of the earnings index, applying this rule for all three time periods and for all three racial/ethnic groups. This reduces the number of CZs we can analyze from 371 to 159. However, these 159 CZs account for 79.6 percent of the U.S. population.

Before we turn to the top CZ lists used above, we first consider, in Table 7, some descriptive statistics and correlations for the three racial/ethnic groups across the 159 CZs. As before, we focus on the change in the natural logarithm of the earnings index over the long horizon, between 2000 and 2015–2019.

The first panel of Table 7 shows that the variation across CZs in the changes in the earnings indices for Black workers and Hispanic workers is much greater than it is for white workers, with standard deviations more than twice as large. As with the sub-BA group, economic fortunes for Black workers and Hispanic workers are more closely tied to their CZ. Individuals with bachelor's degrees, and white non-Hispanic workers, have seen more uniform trends across places.

Table 7 Selected CZ-level Statistics for Changes in Indices of Real Median Annual Earnings, 2000 to 2015–2019, for Racial/Ethnic Groups

Standard deviation of earnings index changes across CZs		
White	*Black*	*Hispanic*
7.8%	18.6%	17.1%
Cross-correlations of CZ earnings index changes across racial/ethnic groups		
White and Black	*White and Hispanic*	*Black and Hispanic*
0.379	0.258	0.371
Cross-correlations of CZ earnings index changes across racial/ethnic and education groups		
White & Sub-BA		*White & BA*
0.886		0.711
Black & Sub-BA		*Black and BA*
0.549		0.303
Hispanic & Sub-BA		*Hispanic & BA*
0.403		0.279

NOTE: These statistics are calculated over the 159 CZs that have at least 100 cases in the underlying microdata sample for determining the annual earnings index for each ethnic group and time period. These 159 CZs account for 79.6 percent of the U.S. population as of 2000.

Indeed, the second panel shows that changes in the earnings indices are only modestly correlated across the different racial/ethnic groups. The third panel expands on these divergences across areas by comparing correlations between the race/ethnic groups and the education groups. Changes in the Black and Hispanic earnings indices are more highly correlated with changes in the sub-BA earnings index than with changes in the BA+ earnings index, but the difference in correlations is only moderate. Interestingly, this pattern also holds for white non-Hispanic workers and the education groups, but the overall correlations are much higher (in part reflecting the greater sizes of these groups). The bottom line: unlike for white non-Hispanic workers, a CZ's earnings growth success with Black workers and Hispanic workers cannot simply be predicted by that CZ's performance with other groups, such as those with less education.

What CZs have seen the strongest and weakest earnings growth for each of the racial/ethnic groups? Tables 8, 9, and 10 report top-ranked and bottom-ranked CZs by growth in the earnings index over the 2000 to 2015–2019 period. Table 8 ranks by Black earnings gains, Table 9 by Hispanic earnings gains, and Table 10 by white non-Hispanic earnings gains. In each case, we also present earnings index gains for the other racial/ethnic groups to facilitate comparisons.

These three tables reflect that earnings gains of different racial groups often have little to do with one another. For example, Salt Lake City, Providence, and Boston have produced significant gains in the Black earnings index, even though the earnings index gains for whites are modest (Table 8). On the other hand, Pittsburgh, San Francisco, and Albany have produced sizable white earnings index gains, but these gains have not been shared by Black workers (Table 10).

Even among cities thought of as "similar" high-tech cities, racial earnings differentials often have evolved differently. For example, although San Francisco shows a sizable Black earnings disadvantage versus white workers, other high-tech cities such as Seattle and Minneapolis-St. Paul have shared earnings gains broadly across diverse racial groups. Some regional clustering seems to be evident. For example, several upstate New York cities (Albany, Rochester, Syracuse) show a pattern of losses for Black workers but gains for white workers.

Table 8 Top 5 and Bottom 5 CZs Earnings Index Changes between 2000 and 2015–2019, by Size Class, Ranked by Black Earnings Index Changes

		Largest city	2000 pop (millions)	Black earnings change	Hispanic earnings change	White earnings change
Panel A: CZs ≥1M in 2000 pop.						
Top 5	Salt Lake, UT	Salt Lake City	1.826	29.7%	6.5%	4.4%
	Providence, RI	Providence	1.583	21.4%	7.4%	1.0%
	Hennepin, MN	Minneapolis	2.946	16.8%	9.8%	5.9%
	Oklahoma, OK	Oklahoma City	1.107	15.7%	−1.4%	6.2%
	Middlesex, MA	Boston	4.752	13.8%	6.7%	3.1%
Bottom 5	San Joaquin, CA	Stockton	1.267	−18.5%	6.1%	−5.0%
	Albany, NY	Albany	1.171	−21.1%	−1.8%	6.5%
	Monroe, NY	Rochester	1.096	−21.3%	−29.5%	5.5%
	Onondaga, NY	Syracuse	1.032	−26.1%	−33.7%	6.1%
	Kern, CA	Bakersfield	1.159	−46.8%	−9.3%	−13.4%
Panel B: CZ 500K–1M in 2000 pop.						
Top 5	El Paso, TX	El Paso	0.871	35.3%	2.1%	−12.8%
	Polk, IA	Des Moines	0.507	30.9%	21.6%	6.8%
	Escambia, FL	Pensacola	0.623	27.0%	−1.6%	5.5%
	Douglas, NE	Omaha	0.803	25.0%	−0.6%	7.7%
	Volusia, FL	Deltona	0.563	23.4%	−31.7%	−15.6%
Bottom 5	Genesee, MI	Flint	0.956	−24.4%	−27.5%	−16.3%
	Luzerne, PA	Scranton	0.793	−28.8%	−41.9%	5.6%
	Sarasota, FL	North Port	0.764	−32.9%	−14.6%	−10.9%
	Polk, FL	Lakeland	0.598	−43.1%	−18.9%	−24.7%
	Saginaw, MI	Saginaw	0.541	−43.1%	9.2%	−10.2%
Panel C: CZ 100–500K in 2000 pop.						
Top 5	Hunt, TX	Greenville	0.186	48.4%	1.8%	21.2%
	Taylor, TX	Abilene	0.174	36.7%	6.4%	6.3%
	Scott, IA	Davenport	0.457	31.8%	−2.8%	3.5%
	Sebastian, AR	Fort Smith	0.329	30.8%	0.7%	0.4%
	Etowah, AL	Gadsden	0.328	26.1%	16.8%	−13.1%
Bottom 5	Jefferson, TX	Beaumont	0.498	−38.6%	−104.6%	−9.7%
	Potter, TX	Amarillo	0.258	−50.0%	0.0%	7.2%
	Anderson, TX	Palestine	0.110	−68.6%	−66.6%	−19.4%
	Lowndes, GA	Valdosta	0.227	−68.7%	−18.4%	−17.2%
	Wichita, TX	Wichita Falls	0.156	−70.0%	−32.3%	−1.2%

NOTE: See note to Table 4.

Table 9 Top 5 and Bottom 5 CZs Earnings Index Changes between 2000 and 2015–2019, by Size Class, Ranked by Hispanic Earnings Index Changes

		Largest city	2000 pop (millions)	Black earnings change	Hispanic earnings change	White earnings change
Panel A: CZs ≥1M in 2000 pop						
Top 5	Multnomah, OR	Portland	1.928	4.8%	13.0%	−2.0%
	Jackson, MO	Kansas City	1.714	11.5%	11.4%	0.0%
	Jefferson, KY	Louisville	1.101	9.8%	10.6%	3.7%
	Marion, IN	Indianapolis	1.689	−5.8%	10.2%	−1.3%
	Tarrant, TX	Dallas	1.785	5.5%	9.8%	2.3%
Bottom 5	Duval, FL	Jacksonville	1.176	5.1%	−17.1%	−2.4%
	Montgomery, OH	Dayton	1.133	9.0%	−18.3%	2.7%
	Erie, NY	Buffalo	1.408	12.4%	−21.6%	6.1%
	Monroe, NY	Rochester	1.096	−21.3%	−29.5%	5.5%
	Onondaga, NY	Syracuse	1.032	−26.1%	−33.7%	6.1%
Panel B: CZ 500K–1M in 2000 pop						
Top 5	Polk, IA	Des Moines	0.507	30.9%	21.6%	6.8%
	Santa Barbara, CA	Santa Maria	0.646	−0.9%	16.3%	4.0%
	Allen, IN	Fort Wayne	0.548	−7.2%	16.3%	−1.8%
	Newport News, VA	Newport News	0.508	5.2%	15.2%	−0.4%
	Horry, SC	Myrtle Beach	0.620	5.2%	11.8%	−27.6%
Bottom 5	Peoria, IL	Peoria	0.583	13.0%	−27.6%	−2.5%
	Volusia, FL	Deltona	0.563	23.4%	−31.7%	−15.6%
	Pulaski, AR	Little Rock	0.631	5.0%	−35.1%	1.9%
	Luzerne, PA	Scranton	0.793	−28.8%	−41.9%	5.6%
	Richmond, GA	Augusta	0.534	−7.0%	−42.4%	−10.3%
Panel C: CZ 100–500K in 2000 pop						
Top 5	Bibb, GA	Macon	0.389	−8.8%	29.0%	−16.8%
	Clarke, GA	Athens	0.255	−8.6%	20.7%	−16.4%
	Gregg, TX	Longview	0.396	23.5%	18.7%	3.4%
	Anchorage, AK	Anchorage	0.379	20.0%	18.6%	4.4%
	Etowah, AL	Gadsden	0.328	26.1%	16.8%	−13.1%
Bottom 5	Wichita, TX	Wichita Falls	0.156	−70.0%	−32.3%	−1.2%
	Calcasieu, LA	Lake Charles	0.336	−16.3%	−45.5%	9.6%
	Anderson, TX	Palestine	0.110	−68.6%	−66.6%	−19.4%
	Angelina, TX	Lufkin	0.238	−13.9%	−72.1%	−31.5%
	Jefferson, TX	Beaumont	0.498	−38.6%	−104.6%	−9.7%

NOTE: See note to Table 4.

Table 10 Top 5 and Bottom 5 CZs Earnings Index Changes between 2000 and 2015–2019, by Size Class, Ranked by non-Hispanic White Earnings Index Changes

		Largest city	2000 pop (millions)	Black earnings change	Hispanic earnings change	White earnings change
Panel A: CZs ≥1M in 2000 pop						
Top 5	Allegheny, PA	Pittsburgh	2.603	−3.2%	−3.1%	12.7%
	Hillsborough, NH	Manchester	1.193	2.4%	6.4%	9.3%
	Alameda, CA	San Francisco	5.101	−8.4%	4.8%	8.7%
	King, WA	Seattle	3.942	4.3%	8.6%	7.8%
	Albany, NY	Albany	1.171	−21.1%	−1.8%	6.5%
Bottom 5	Wayne, MI	Detroit	5.077	−15.7%	−3.5%	−9.7%
	Miami-Dade, FL	Miami	3.956	−7.4%	−12.8%	−10.1%
	Los Angeles, CA	Los Angeles	16.373	−6.5%	−4.3%	−12.7%
	Fresno, CA	Fresno	1.651	−0.6%	−0.8%	−13.1%
	Kern, CA	Bakersfield	1.159	−46.8%	−9.3%	−13.4%
Panel B: CZ 500K–1M in 2000 pop						
Top 5	Dane, WI	Madison	0.683	−5.9%	8.8%	7.9%
	Denton, TX	Denton	0.542	0.6%	−1.3%	7.8%
	Douglas, NE	Omaha	0.803	25.0%	−0.6%	7.7%
	Polk, IA	Des Moines	0.507	30.9%	21.6%	6.8%
	Luzerne, PA	Scranton	0.793	−28.8%	−41.9%	5.6%
Bottom 5	Genesee, MI	Flint	0.956	−24.4%	−27.5%	−16.3%
	Muscogee, GA	Columbus	0.545	−11.6%	−24.4%	−16.7%
	Brevard, FL	Palm Bay	0.589	−2.1%	−19.9%	−16.9%
	Polk, FL	Lakeland	0.598	−43.1%	−18.9%	−24.7%
	Horry, SC	Myrtle Beach	0.620	5.2%	11.8%	−27.6%
Panel C: CZ 100–500K in 2000 pop						
Top 5	Hunt, TX	Greenville	0.186	48.4%	1.8%	21.2%
	Calcasieu, LA	Lake Charles	0.336	−16.3%	−45.5%	9.6%
	Comanche, OK	Lawton	0.181	20.7%	−23.1%	8.8%
	Victoria, TX	Victoria	0.184	20.1%	7.5%	8.5%
	Lubbock, TX	Lubbock	0.300	15.7%	−2.9%	7.8%
Bottom 5	Bibb, GA	Macon	0.389	−8.8%	29.0%	−16.8%
	Lowndes, GA	Valdosta	0.227	−68.7%	−18.4%	−17.2%
	Anderson, TX	Palestine	0.110	−68.6%	−66.6%	−19.4%
	Catawba, NC	Hickory	0.342	−16.6%	−8.3%	−20.5%
	Angelina, TX	Lufkin	0.238	−13.9%	−72.1%	−31.5%

NOTE: See note to Table 4.

5. REGRESSION ANALYSIS OF LOCAL CORRELATES OF LABOR MARKET SUCCESS FOR DIVERSE GROUPS

Our examination of local labor market trends now turns to some descriptive regressions. These regressions aim to explain which baseline characteristics of local labor markets correlate with changes in these market outcomes. We first describe our predictor variables and then focus on showing summary results from the regressions for CZ earnings changes over the 2000 to 2015–2019 period, both for changes overall and for various groups. We next compare these results for annual earnings with analogous results for the other labor market outcomes, changes in employment rates and real hourly wages. We also make some comparisons with the shorter time intervals (2000 to 2005–2007 and 2005–2007 to 2015–2019). Finally, we briefly compare the CZ-based regressions to those from CBSAs.

Descriptions of Predictor Variables

The predictor variables are listed in Table 11. These include the local labor market's baseline population, its region of the country, its age mix, socioeconomic and racial/ethnic composition, and various characteristics that describe levels or changes in labor demand conditions.

Population and region of the country could reflect a wide variety of labor demand or supply conditions that might affect local labor market outcomes. Age mix reflects that even though our labor market outcomes adjust for demographic mix, demographic factors may spill over and affect other groups; for example, the size of older cohorts may affect the productivity and earnings of younger cohorts through career ladders.

Table 11 Predictor Variables for Regressions on CZ-Level Annual Earnings Growth

Variable	Definition	Mean	SD	10th ptile	Median	90th ptile
Log population	Natural log of CZ population	12.82	1.021	11.74	12.55	14.35
(Log population)^2	Square of log population	165.3	27.23	137.8	157.5	206.0
New England	Indicators for each Census Division (East North Central is omitted category)	0.032	0.177			
Mid-Atlantic		0.062	0.241			
West North Central		0.116	0.321			
South Atlantic		0.208	0.406			
East South Central		0.127	0.333			
West South Central		0.137	0.345			
Mountain		0.078	0.269			
Pacific		0.076	0.265			
Pop share aged 25–34	Share of CZ population aged 25–64 that is aged 25–34 (age group 55–64 is omitted category)	0.254	0.026	0.224	0.253	0.285
Pop share aged 35–44	Share of CZ population aged 25–64 that is aged 35–44	0.306	0.013	0.289	0.306	0.321
Pop share aged 45–54	Share of CZ population aged 25–64 that is aged 45–54	0.262	0.016	0.244	0.262	0.280
Black pop share	Share of CZ population aged 25–64 that is Black	0.097	0.111	0.005	0.052	0.285
Hispanic pop share	Share of CZ population aged 25–64 that is Hispanic	0.066	0.117	0.008	0.024	0.154
BA+ pop share	Share of CZ population aged 25–64 that has at least a bachelor's degree	0.212	0.066	0.133	0.202	0.306
Bartik shock, 1999–2016	Predicted growth in CZ employment	0.122	0.079	0.020	0.127	0.205
CZ relative emp. ratio	Natural log of ratio of adjusted CZ employment rate to national employment rate	−0.013	0.059	−0.074	−0.004	0.049
Bartik * rel. emp. ratio	Interaction between Bartik shock and relative emp. ratio	−0.002	0.007	−0.011	−0.0003	0.006
Bartik wage, 1999–2016	Predicted growth in CZ wage premium	0.005	0.012	−0.008	0.006	0.018

NOTE: All explanatory variables are measured in year 2000 unless otherwise noted; see text for descriptions. Statistics shown are for the full sample of 371 CZs; samples for Black and Hispanic residents are based on fewer CZs with sufficient populations, but statistics are generally similar. SD indicates standard deviation.

Other demographic characteristics, such as the Black or Hispanic shares of the population, or the share with at least a bachelor's degree, may similarly influence labor demand or labor supply through spillover effects. On the demand side, any of these factors could alter the number and types of jobs attracted to or growing in the local economy. These characteristics also could proxy for the area's skill base, which could have its own spillover effects. Additionally, the share of residents who are Black or Hispanic could relate to latent discriminatory practices or political polarization that affect labor market outcomes (Smith, Kreitzer, and Suo 2020).

The remaining characteristics proxy for levels or changes in labor demand conditions. The "Bartik shock" measures predicted job growth based on the local labor market's mix of industries in a baseline year and national growth rates (over some horizon) for each industry. It effectively asks by what percentage would the number of jobs in a local labor market have increased if each industry in the local area had grown at its national average rate over a given time period. As documented in Bartik (1991), this measure proxies for external demand shocks to a local labor market area's export-base industries.[18]

The base year ratio of the adjusted employment rate in the local labor market to that of the nation (in natural logarithm) reflects the relative strength of baseline labor market conditions, whether from greater demand, supply, or both. These baseline labor market conditions might directly affect subsequent labor market outcome trends for a couple of reasons. First, such conditions could be persistent, perhaps reflecting effective governance or institutions shaping work ethics (Veblen 1899; Weber 1930), or there could be reversion to the mean if initial conditions were unusually strong or weak. Second, stronger baseline labor market conditions

[18] Appendix B presents the specific formula for the Bartik shock.

might correlate with fewer social problems and stronger fiscal conditions, which might independently influence labor market trends.

Predicted job growth and baseline labor market conditions, moreover, might produce interactive effects, either negative or positive. On the negative side, for example, predicted job growth might be associated with greater employment rate increases when there initially is a greater concentration of nonemployed persons (that is, baseline labor market conditions are weak). On the positive side, predicted job growth might correlate with stronger local earnings growth when labor demand pressures are already high relative to labor supply at baseline.

The "Bartik wage shock" represents an alternative mechanism through which initial local industry mix and national industry growth can affect subsequent local labor market conditions—namely, through the role of industry mix on wages. This measure starts with estimates of national industry wage premia, how much average pay in an industry compares with the overall national average pay, controlling for the demographic and educational mix of the workforce. We apply these national industry wage premia from the baseline period to each area's baseline local industry mix to construct the area's baseline expected wage premium. We construct an analogous measure for the end period using the end period national industry wage premia, the *baseline* local industry mix, and national industry growth trends from the base period to the final period; that is, we simulate how each area's industry mix would change if each industry grew at its national rate, and then apply these updated industry mix shares to the end period industry wage premia. We finally take the difference between these predicted wage premia measures, the end period minus the base period, as the variable we include in the regression. The variable captures the extent to which an area's overall wage is expected to change over time from both evolving industry mix and wage change within industries.[19]

Explaining Changes in CZ Earnings for Different Groups, 2000 to 2015–2019

We focus on regressions that seek to explain earnings trends across CZs between 2000 and 2015–2019. As mentioned previously, we view trends in annual earnings as the best "bottom line" measure for the evolution of labor market outcomes, as they reflect changes in employment rates, work hours, and hourly wages. Earnings are also measured over the entire preceding year in the underlying data, whereas employment rates are measured at a single point in time. Furthermore, annual earnings are reported directly, whereas real hourly wages must be constructed from both observed annual earnings and plausible inferences about annual work hours. Finally, as shown in the preceding section, changes in real earnings have greater variation across CZs than do changes in employment rates or real hourly wages.

We also choose to focus on CZs rather than metro areas (CBSAs) because our set of CZs, even when restricted to those with more than 100,000 population in the year 2000, encompass more of the total U.S. population than do metro areas, and also include most of the country's rural population.[20]

Finally, the long horizon from 2000 to 2015–2019 better captures secular trends than do the shorter horizons, between 2000 and 2005–2007 or between 2005–2007 and 2015–2019. The former period, for example, could reflect the effects of the U.S. economy going into a real estate

[19] A value of 0.10 for this variable, for example, indicates wages would be expected to rise by about 10 percent due to expected changes in industry mix and changes in average industry-specific wage premia. Appendix B gives a formal definition of this predicted wage change variable.

[20] Nonetheless, the descriptive relationships we find with CZ-based regressions generally hold for metro areas as well.

bubble, while the latter period might reflect the recovery from that bubble. Long-run trends are of greater research and policy interest.

Table 12 shows the regression results for this initial summary regression. Starting with the column pertaining to earnings changes for all residents, we note little correlation with the initial size of the CZ, but interesting variations by region, with the Mid-Atlantic and West North Central divisions significantly outperforming the (omitted) East North Central division, while the South Atlantic lagged behind. The initial age distribution also matters, with CZs that have a greater share of 35–44-year-olds, as compared to 55–64-year-olds, exhibiting greater earnings growth between 2000 and 2015–2019. This could reflect genuine effects of this age group on worker productivity—workers 35–44 in 2000 would be 50–63 in 2015–2019, near peak earnings and presumed productivity—but it could also reflect that younger age groups were attracted to specific CZs that had done better in the past and that might continue to do so in the future.

Perhaps the most disturbing result is that CZs with greater Black shares of their population, conditional on the other characteristics in the table, show slower earnings growth. The coefficient estimate is highly statistically significant, over six times its standard error, and it implies that, other characteristics held the same, a CZ with a 10 percentage point greater Black share of its population would be predicted to have real annual earnings growth of 3.5 percentage points less over the nearly two-decade period. For context, this amounts to about 27 percent of the difference in earnings growth between the 25th and 75th percentiles of CZs. The combination of demand and supply forces that may drive this result is unknown and deserves further study.

Table 12 Area Characteristics that Predict Changes in CZ-Level Annual Earnings, 2000–2017

Characteristic	All residents	Sub-BA	BA+	Black residents	Hispanic residents	White residents
Log population	−0.0143	0.0500	0.0223	0.5900*	0.2182	−0.0153
	(0.0914)	(0.1362)	(0.0704)	(0.3101)	(0.2546)	(0.0835)
(Log population)^2	0.0000	−0.0026	−0.0014	−0.0207*	−0.0085	0.0000
	(0.0034)	(0.0050)	(0.0026)	(0.0111)	(0.0093)	(0.0031)
Division:						
New England	−0.0159	−0.0262	0.0041	−0.0044	0.1979***	−0.0135
	(0.0182)	(0.0288)	(0.0139)	(0.0697)	(0.0711)	(0.0178)
Mid-Atlantic	0.0363**	0.0622***	−0.0079	−0.0380	0.0775	0.0400***
	(0.0149)	(0.0239)	(0.0131)	(0.0575)	(0.0750)	(0.0149
West North Central	0.0394**	0.0432**	0.0474***	0.1123	0.1133*	0.0428***
	(0.0156)	(0.0219)	(0.0137)	(0.0781)	(0.0659)	(0.0153)
South Atlantic	−0.0330**	−0.0356	−0.0553***	−0.0102	−0.0125	−0.0379**
	(0.0151)	(0.0235)	(0.0147)	(0.0688)	(0.0571)	(0.0151)
East South Central	−0.0030	−0.0002	−0.0350**	0.0827	0.0566	−0.0125
	(0.0165)	(0.0248)	(0.0166)	(0.0715)	(0.0648)	(0.0154)
West South Central	0.0310	0.0346	0.0144	0.1070	−0.0060	0.0323*
	(0.0189)	(0.0284)	(0.0145)	(0.0719)	(0.0623)	(0.0183)
Mountain	0.0098	−0.0047	0.0341	−0.0020	0.0102	0.0203
	(0.0298)	(0.0477)	(0.0241)	(0.0720)	(0.0730)	(0.0259)
Pacific	0.0061	−0.0136	0.0237	−0.0185	0.1110*	−0.0138
	(0.0227)	(0.0310)	(0.0223)	(0.0594)	(0.0587)	(0.0220)
Pop share aged 25–34	−0.0464	0.4033	−0.5886	0.4291	0.1843	0.0567
	(0.3696)	(0.5922)	(0.4391)	(1.3305)	(0.8684)	(0.3403)
Pop share aged 35–44	1.0871**	1.6460**	0.7990*	0.2869	1.1778	1.3623***
	(0.4636)	(0.7020)	(0.4721)	(1.5928)	(1.3038)	(0.4123)
Pop share aged 45–54	0.3657	1.0394	−0.8899	1.2548	−1.2551	0.3772
	(0.6639)	(1.0954)	(0.7226)	(2.4370)	(1.4624)	(0.6035)
Black pop share	−0.3500***	−0.5906***	−0.0200	−0.3927**	−0.1114	−0.2861***
	(0.0553)	(0.0903)	(0.0451)	(0.1926)	(0.1926)	(0.0530)
Hispanic pop share	−0.0553	−0.0910	−0.0714*	0.1199	0.1843*	−0.1071*
	(0.0583)	(0.1020)	(0.0380)	(0.1974)	(0.1037)	(0.0547)
BA+ pop share	0.0597	−0.1613	0.5428***	0.3440	0.4890	0.1325
	(0.1302)	(0.2080)	(0.0935)	(0.3657)	(0.3331)	(0.1256)
Bartik shock, 1999–2016	0.2239**	0.3860**	−0.0615	0.1305	0.0812	0.1688*
	(0.1088)	(0.1559)	(0.0586)	(0.2893)	(0.2930)	(0.0916)
CZ relative emp. ratio	0.7538***	1.1350***	0.3027	0.4291	0.7060	0.6611***
	(0.2004)	(0.2733)	(0.2536)	(0.3644)	(0.4887)	(0.1839)
Bartik × rel. emp. ratio	0.2803	0.5905	−2.1235	−0.1159	−0.5197	−0.1803
	(1.5134)	(1.9509)	(1.3496)	(2.3323)	(3.3644)	(1.4971)
Bartik wage, 1999–2016	0.9494**	1.3576*	−0.2013	−1.5001	−1.4022	0.9151**
	(0.4624)	(0.7515)	(0.4472)	(2.0905)	(1.8811)	(0.4446)
Observations	371	371	371	239	246	371
R^2	0.5075	0.5009	0.4029	0.2230	0.2552	0.5122

NOTE: Each column represents a separate regression with a different sample or group of commuting zone residents (all restricted to aged 25–64). All explanatory variables are measured in year 2000 unless otherwise noted; see text for descriptions. The omitted Census division is East North Central; the omitted age group is 55–64. Standard errors robust to heteroskedasticity appear below coefficient estimates. ***, **, * imply p-values less than 0.01, 0.05, and 0.10, respectively.

The various demand condition variables (Bartik shocks and relative employment ratios) have the expected signs. Areas with an initial industry mix that predicts stronger job growth demonstrate higher earnings growth: areas with 10 percent greater predicted job growth witness additional real earnings growth of 2.2 percent. The predicted wage premium growth has about a one-for-one relationship with earnings growth, with every 1 percent greater predicted wage premium translating to 0.94 percent faster earnings growth. Additionally, the relative employment rate ratio also strongly predicts annual earnings growth: when the CZ's baseline employment rate is 10 percent higher than that of the nation, the CZ's subsequent earnings growth is on average about 7.5 percent greater. This implies that CZs that started with tight labor markets tended to experience faster earnings gains, although the relatively small and imprecise coefficient estimate on the interaction with the Bartik shock suggests that predicted job growth did not mediate the role of a tight labor market.

The remaining columns of Table 12 show analogous results by education and racial groups. The patterns of coefficients indicate that different groups are affected quite differentially by different predictors. Consider first the two education groups, for residents with less than a bachelor's degree and residents with a bachelor's or advanced degree. The most dramatic difference is that the share of the population that is Black has a very strong correlation with earnings growth for residents with less than a bachelor's degree, but essentially no correlation with earnings growth for residents with at least a bachelor's degree. Apparently, whatever demand and supply forces are captured by the Black share of the population—net of the other characteristics—are irrelevant for earnings growth of residents with extensive education.

Another large difference is that the share of residents with at least a bachelor's degree has a strong positive correlation with earnings growth of the same demographic, with a 10 percentage point higher baseline share implying 5.4 percent additional earnings gains. In contrast, this share has a negative correlation with earnings growth for the less-educated group, although the coefficient is imprecisely estimated. These patterns accord with the idea that the highly educated may see advantages in productivity when they are more concentrated geographically (Glaeser and Gottlieb 2009). However, such productivity advantages—at least as captured by earnings growth—do not seem to spill over to less-educated residents.

Finally, labor demand conditions have strong positive correlations with the earnings growth of residents with less than a bachelor's degree but not those with a bachelor's or more. Predicted job growth or wage growth based on industry mix, and baseline relative employment rates, have a minimal relationship with the earnings growth of highly educated residents.

The latter three columns of Table 12 show the correlates of earnings growth by racial and ethnic group. Among Black residents, local demand conditions and most other characteristics seem to have little association, although these coefficients are somewhat noisy. The only factor with a large and precise relationship is the Black share of the population; this correlation is strongly negative, with a 10 percentage point greater share in the baseline Black population associated with 3.9 percent less earnings growth, slightly greater in magnitude than the 3.5 percent slower earnings growth among all residents.

For Hispanic residents, as well, relatively few characteristics have clear correlations with earnings growth, and precision again is an issue. Hispanics living in New England experienced faster earnings growth than in other regions of the country, with more modest advantages in the Upper Plains and the West Coast. Earnings in contrast to the results for Black residents, a greater concentration in the CZ of the own group is associated with greater earnings gains for Hispanic residents, as a 10 percentage point greater Hispanic share of the baseline population translates to 1.9 percent faster earnings growth.[21]

Finally, we note that white residents, as the largest racial group, generally show patterns of coefficients close to that for all residents in the first column. In particular, earnings growth for white residents correlates with the local demand indicators, in contrast with both Black and Hispanic residents. Growth in labor demand thus is not "inclusive" of disadvantaged ethnic groups, even though it *is* "inclusive" of less-educated residents. More broadly, the pattern of results for disadvantaged ethnic groups does not resemble the pattern of results for the disadvantaged education group. Therefore, policymakers and researchers should not assume that the local factors associated with labor market success for less-educated groups will necessarily help disadvantaged racial and ethnic groups. Furthermore, the fact that we *do* see substantial differences in earnings growth across places for disadvantaged racial and ethnic groups (Tables 8 and 9) suggests that this variation is not due to easily observed demographic and economic fundamentals but instead may relate to "softer" factors that policymakers could more readily influence. We return to this possibility in the case studies section below.

Results for Employment Rates and Real Wage Rates

Although the results for real annual earnings are, in our view, the most important results, we have also examined correlates with changes in local employment rates and real hourly wages. Tables 13A and 13B summarize these change relationships for a key subset of characteristics for CZs between 2000 and 2015–2019. For comparison, we also include results for annual earnings (taken from Table 12), and we again show breakdowns among different groups of residents.

[21] Interestingly, this same variable has *negative* correlation with earnings growth for white residents, although the magnitude is modest.

Table 13A Area Characteristics that Predict Changes in CZ-Level Annual Earnings, Employment Rates, and Hourly Earnings, 2000–2017, for All Residents and by Education

Characteristic	*Everyone*			*Sub-BA group*			*BA+ group*		
	Annual earnings	Emp. rates	Hourly wages	Annual earnings	Emp. rates	Hourly wages	Annual earnings	Emp. rates	Hourly wages
Black pop share	−0.3499***	−0.0956***	−0.0325	−0.5906***	−0.1146***	−0.0395	−0.0200	−0.0443***	0.0037
	(0.0553)	(0.0201)	(0.0226)	(0.0903)	(0.0229)	(0.0266)	(0.0451)	(0.0167)	(0.0300)
Hispanic pop share	−0.0555	−0.0191	−0.0199	−0.0910	−0.0268	−0.0138	−0.0714*	−0.0017	−0.0572**
	(0.0582)	(0.0207)	(0.0171)	(0.1020)	(0.0254)	(0.0231)	(0.0380)	(0.0161)	(0.0283)
BA+ pop share	0.0596	0.0905**	0.0234	−0.1613	0.0968*	−0.1471***	0.5428***	0.1420***	0.4126***
	(0.1303)	(0.0423)	(0.0471)	(0.2080)	(0.0547)	(0.0541)	(0.0935)	(0.0292)	(0.0617)
Bartik shock, 1999–2016	0.2237**	0.0605**	−0.0196	0.3860**	0.0736**	0.0623**	−0.0615	−0.0277	−0.1496***
	(0.1088)	(0.0294)	(0.0275)	(0.1559)	(0.0366)	(0.0299)	(0.0586)	(0.0205)	(0.0391)
CZ relative emp. ratio	0.7538***	0.0179	0.1908***	1.1350***	0.0462	0.2034***	0.3027	−0.5261***	0.3601**
	(0.2003)	(0.0744)	(0.0469)	(0.2733)	(0.0749)	(0.0496)	(0.2536)	(0.0728)	(0.1773)
Bartik × rel. emp. ratio	0.2804	−0.4928	−0.6569*	0.5905	−0.5240	−0.6372*	−2.1235	0.6443*	−2.0503*
	(1.5130)	(0.6006)	(0.3964)	(1.9509)	(0.5999)	(0.3789)	(1.3496)	(0.3889)	(1.0672)
Bartik wage, 1999–2016	0.9364**	0.1215	0.6236***	1.3576*	0.1857	0.6555***	−0.2013	−0.1611	0.2825
	(0.4582)	(0.1554)	(0.1599)	(0.7515)	(0.1792)	(0.1768)	(0.4472)	(0.1444)	(0.2714)

Table 13B Area Characteristics that Predict Changes in CZ-Level Annual Earnings, Employment Rates, and Hourly Earnings, 2000–2017, by Race and Ethnicity

Characteristic	*Black residents*			*Hispanic residents*			*White residents*		
	Annual earnings	Emp. rates	Hourly wages	Annual earnings	Emp. rates	Hourly wages	Annual earnings	Emp. rates	Hourly wages
Black pop share	−0.3927**	0.0243	−0.1289*	−0.1114	−0.0854	0.2419**	−0.2861***	−0.0672***	−0.0192
	(0.1926)	(0.0878)	(0.0693)	(0.1926)	(0.0529)	(0.0980)	(0.0530)	(0.0162)	(0.0234)
Hispanic pop share	0.1199	0.1760**	0.1181	0.1843*	0.0148	0.0301	−0.1071*	-0.0142	−0.0183
	(0.1974)	(0.0854)	(0.0882)	(0.1037)	(0.0338)	(0.0424)	(0.0547)	(0.0205)	(0.0185)
BA+ pop share	0.3440	0.5613***	−0.1558	0.4890	0.3111***	0.0493	0.1325	0.0854**	0.0566
	(0.3657)	(0.1612)	(0.1136)	(0.3331)	(0.1176)	(0.1606)	(0.1256)	(0.0388)	(0.0499)
Bartik shock, 1999–2016	0.1305	0.0056	0.0640	0.0812	0.1572**	0.0995	0.1688*	0.0474*	−0.0390
	(0.2893)	(0.0965)	(0.0888)	(0.2930)	(0.0670)	(0.1206)	(0.0916)	(0.0286)	(0.0261)
CZ relative emp. ratio	0.4291	−0.4800**	0.0931	0.7060	−0.2741***	0.0963	0.6611***	0.0177	0.1647***
	(0.3644)	(0.2209)	(0.1248)	(0.4887)	(0.1005)	(0.2142)	(0.1839)	(0.0762)	(0.0524)
Bartik × rel. emp. ratio	−0.1159	0.5982	−0.4077	−0.5197	−0.6271	−0.5044	−0.1803	−0.6554	−0.7433*
	(2.3323)	(1.4689)	(0.7209)	(3.3644)	(0.6540)	(1.3567)	(1.4971)	(0.6033)	(0.4285)
Bartik wage, 1999–2016	−1.5001	−0.6482	1.0168*	−1.4022	−0.3679	−0.8354	0.9151**	0.2179	0.5965***
	(2.0905)	(0.7219)	(0.5478)	(1.8811)	(0.4235)	(0.9829)	(0.4446)	(0.1404)	(0.1670)

NOTE: Each column represents a separate regression with a different outcome change (real annual median earnings, employment rates, real hourly wages, all as previously described in the text) for a different group of CZ residents aged 25–64. All explanatory variables are measured in year 2000 unless otherwise noted; see text for descriptions. All regressions also include the additional variables shown in Table 12 even though these estimates are not shown. Observation counts are as in Table 12. Standard errors robust to heteroskedasticity appear below coefficient estimates. ***, **, * imply p-values less than 0.01, 0.05, and 0.10, respectively.

The results support the interpretation that the earnings results are more reliable and useful for policy inference. The relationships between baseline characteristics and changes in employment rates and hourly wages tend to be imprecise relative to the correlations with changes in annual earnings. Additionally, it is clear that the latter correlations capture key nuances of labor market outcomes not present with employment rate or hourly wages. For example, take the coefficient estimate at the top left of Table 13A for the Black population share among "everyone." The magnitude of this estimate vastly exceeds the sum of the estimates for the employment rate and hourly wages in the next two columns. Under our logarithmic specification, if employment rates and hourly wages sufficiently categorized total annual earnings (e.g., if hours worked did not vary), the sum of their coefficients would equal that of annual earnings. The implication is that our construction of annual earnings also captures important variation in work intensity not available in the other measures.

Nonetheless, the additional outcomes do shed some light on the channels, or mechanisms, through which the correlates can predict changes in annual earnings. For example, a larger share of residents with at least a bachelor's degree at baseline is associated with gains in employment rates for all the demographic groups, but with hourly wage gains only for residents who also have at least a bachelor's degree; wages for residents without a bachelor's degree even show a robust negative correlation. This might imply that a more highly educated share of the population predicts faster job growth for residents (net of immigration to the area), but that these additional jobs don't pay especially well, or have steady hours, unless the worker is also highly educated. Likewise, the Bartik predicted job growth shock tends to correlate to higher earnings growth more through job growth than wage growth, while the reverse is true for the Bartik predicted wage growth shock; this is reassuring. In contrast, the relative employment ratio has a stronger correlation with earnings growth through gains in hourly wages than through increases in employment rates. In fact, for some groups (Black residents, Hispanic residents, and even those with bachelor's degrees), the correlation between the initial relative employment ratio and the change in employment rate is statistically significantly negative. Although this pattern deserves further investigation, one possibility is the reverse of an "added worker effect" (Stephens 2002): an initially tight labor market puts upward pressure on wages, allowing marginal workers—those with low earnings—to quit their jobs as long as at least one primary earner remains.

Results for Different Time Periods: 2000 to 2015–2019, 2000 to 2005–2007, 2005–2007 to 2015–2019

It can also be illustrative to examine correlations between initial area characteristics and growth in annual earnings over shorter horizons, between 2000 and the period just prior to the Great Recession, or between the period just before the Great Recession and the period prior to the pandemic (2015–2019). Although these subperiod correlations may be distorted by the financial bubble that preceded the Great Recession, and thus may not capture long-term trends well, they can indicate how the business cycle can promote—or retard—economic progress for different groups of residents.

Tables 14A and 14B show the relationships between annual earnings growth and initial CZ characteristics for different groups as in Table 12, but now for both the long horizon (2000 to 2015–2019) and the two, shorter, component horizons.[22]

[22] The coefficient estimates for the two component time periods typically sum approximately to the coefficient estimate for the longer time period. The sum is approximate because the base period of the characteristics varies across the time periods.

Table 14A Area Characteristics that Predict Changes in CZ-Level Annual Earnings, across Multiple Time Horizons, for All Residents and by Education

Characteristic	*Everyone*			*Sub-BA*			*BA+ group*		
	2000–2017	2000–2006	2006–2017	2000–2017	2000–2006	2006–2017	2000–2017	2000–2006	2006–2017
Black pop share	−0.3500***	−0.0850**	−0.2464***	−0.5906***	−0.1316**	−0.4307***	−0.0200	−0.0035	−0.0452
	(0.0553)	(0.0411)	(0.0513)	(0.0903)	(0.0598)	(0.0769)	(0.0451)	(0.0391)	(0.0504)
Hispanic pop share	−0.0553	−0.0695**	0.0573	−0.0910	−0.0391	0.0186	−0.0714*	−0.1392***	0.0614
	(0.0583)	(0.0326)	(0.0565)	(0.1020)	(0.0411)	(0.0906)	(0.0380)	(0.0463)	(0.0440)
BA+ pop share	0.0597	0.0023	0.0817	−0.1613	−0.0723	−0.0833	0.5428***	0.1429*	0.3425***
	(0.1302)	(0.0770)	(0.0981)	(0.2080)	(0.0968)	(0.1626)	(0.0935)	(0.0789)	(0.0806)
Bartik shock	0.2239**	0.3997***	0.0366	0.3860**	0.6623***	0.1229	−0.0615	−0.0688	−0.1068
	(0.1088)	(0.1100)	(0.2241)	(0.1559)	(0.1433)	(0.3239)	(0.0586)	(0.1158)	(0.2053)
CZ relative emp. ratio	0.7538***	0.3219***	0.2133	1.1350***	0.4533***	0.5732**	0.3027	0.1336	−1.0141***
	(0.2004)	(0.1087)	(0.1981)	(0.2733)	(0.1366)	(0.2356)	(0.2536)	(0.2925)	(0.2693)
Bartik × rel. emp. ratio	0.2803	−2.1998*	4.5280*	0.5905	−2.3911	4.8549*	−2.1235	−4.1391*	5.5907***
	(1.5134)	(1.2013)	(2.4257)	(1.9509)	(1.5758)	(2.8121)	(1.3496)	(2.2774)	(2.0322)
Bartik wage	0.9494**	−0.3258	0.1300	1.3576*	−0.1035	0.7086	−0.2013	−0.6023	−1.0444*
	(0.4624)	(0.5985)	(0.6099)	(0.7515)	(0.7772)	(0.9051)	(0.4472)	(0.7463)	(0.6255)

Table 14B Area Characteristics that Predict Changes in CZ-Level Annual Earnings, across Multiple Time Horizons, by Race and Ethnicity

Characteristic	*Black residents*			*Hispanic residents*			*White residents*		
	2000–2017	2000–2006	2006–2017	2000–2017	2000–2006	2006–2017	2000–2017	2000–2006	2006–2017
Black pop share	−0.3927**	0.0657	−0.6231***	−0.1114	0.2694	−0.1507	−0.2861***	−0.0927**	−0.1854***
	(0.1926)	(0.1277)	(0.1857)	(0.1926)	(0.1902)	(0.2387)	(0.0530)	(0.0433)	(0.0568)
Hispanic pop share	0.1199	−0.1066	−0.1730	0.1843*	0.1034	0.2707*	−0.1071*	−0.1112*	0.0058
	(0.1974)	(0.1639)	(0.1263)	(0.1037)	(0.0823)	(0.1529)	(0.0547)	(0.0613)	(0.0710)
BA+ pop share	0.3440	0.0944	0.2713	0.4890	0.2092	0.6378*	0.1325	0.0247	0.1256
	(0.3657)	(0.2686)	(0.2840)	(0.3331)	(0.2635)	(0.3566)	(0.1256)	(0.0801)	(0.0958)
Bartik shock	0.1305	0.8402***	0.7398	0.0812	1.0665***	−1.2313	0.1688*	0.2659**	0.2377
	(0.2893)	(0.3104)	(0.9369)	(0.2930)	(0.3805)	(0.8019)	(0.0916)	(0.1058)	(0.2176)
CZ relative emp. ratio	0.4291	−0.1290	−0.8481***	0.7060	0.9638***	0.0057	0.6611***	0.2528*	0.4196
	(0.3644)	(0.2269)	(0.3179)	(0.4887)	(0.2530)	(0.6051)	(0.1839)	(0.1388)	(0.2630)
Bartik × rel. emp. ratio	−0.1159	0.6478	7.8963**	−0.5197	−6.5355***	0.3826	−0.1803	−2.8632*	1.5265
	(2.3323)	(3.1879)	(3.3191)	(3.3644)	(2.2724)	(7.2707)	(1.4971)	(1.4939)	(3.1036)
Bartik wage	−1.5001	−2.8637	−1.1722	−1.4022	−3.4494	3.3191	0.9151**	−0.0868	−0.3097
	(2.0905)	(2.9641)	(2.3497)	(1.8811)	(2.7878)	(2.6962)	(0.4446)	(0.6317)	(0.5730)

NOTE: Each column represents a separate regression with the outcome of the change in real annual median earnings, as previously described in the text, across the specified time periods, for a different group of CZ residents aged 25–64. (We abbreviate the time horizon 2005–2007 as 2006, and 2015–2019 as 2017.) All explanatory variables are measured in the base year of the specified horizon (2000 or 2005–2007) unless otherwise noted; see text for descriptions. All regressions also include the additional variables shown in Table 12 even though these estimates are not shown. Observation counts are as in Table 12. Standard errors robust to heteroskedasticity appear below coefficient estimates. ***, **, * imply p-values less than 0.01, 0.05, and 0.10, respectively.

A notable feature is that the positive correlation between the share of the population with a bachelor's degree and earnings growth for the same population is robust across time periods and thus relatively insensitive to the financial bubble. Similarly, the negative correlation between the Black share of the population and the earnings growth of less-educated residents and white residents is also robust across the two time periods, again stressing the importance of further investigating—perhaps qualitatively—this pattern. Another feature is that all three of these correlations are more pronounced in the later time period, when the aggregate labor market grew stronger. In contrast, the positive associations with the Bartik predicted job growth are mostly confined to the earlier period, suggesting that industry structure was less influential on earnings growth in the latter—and more broad-based—expansion. In sum, the post–Great Recession economy does appear to have had different implications for earnings growth than the previous peak-to-peak period.

Results for CBSAs vs. CZs

We view the above estimates based on commuting zones (CZs) as our preferred benchmark case, as CZs include a larger proportion of the U.S. population, including relatively rural areas (even under our minimum population threshold of 100,000). Nonetheless, because many economic developers, researchers, and policymakers often consider metro areas, it is useful to compare our benchmark results from CZs to those from CBSAs. Tables 15A and 15B report associations between real annual earnings growth over the long horizon, 2000 to 2015–2019, for both CBSAs and CZs to facilitate comparison.

In general, results are similar, especially those that were especially strong in Table 12. In particular, the positive relationship between earnings growth of residents with a bachelor's degree and the initial share of the population with a bachelor's degree holds for both CBSAs and

CZs. Likewise, the negative relationships between the initial Black share of the population and real earnings growth for residents without a bachelor's, for Black residents, and for white residents, are also robust to the different choice of geography.

However, there are also differences, some of which are subtle. The coefficients on both the Bartik predicted job growth measure and the baseline relative employment ratio tend to be more positive (and statistically different from 0) for CZs than for CBSAs. The opposite pattern occurs for the Bartik predicted wage growth measure, which shows stronger and more positive correlations for CBSAs than CZs. Whereas predicted job growth seems to have a stronger positive association with earnings growth outside of urban areas, predicted wage growth seems to be more tightly linked with earnings growth within them.

Table 15A Area Characteristics that Predict Changes in CZ-Level and CBSA-Level Annual Earnings, between 2000 and 2017, for All Residents and by Education

Characteristic	*All residents*		*Sub-BA*		*BA+*	
	CZ	CBSA	CZ	CBSA	CZ	CBSA
Black pop share	−0.3500***	−0.2854***	−0.5906***	−0.5236***	−0.0200	−0.0188
	(0.0553)	(0.0598)	(0.0903)	(0.0948)	(0.0451)	(0.0604)
Hispanic pop share	−0.0553	−0.1503***	−0.0910	−0.2702***	−0.0714*	−0.1068***
	(0.0583)	(0.0549)	(0.1020)	(0.0853)	(0.0380)	(0.0395)
BA+ pop share	0.0597	0.0916	−0.1613	−0.2997***	0.5428***	0.4588***
	(0.1302)	(0.0842)	(0.2080)	(0.1075)	(0.0935)	(0.0894)
Bartik shock, 1999–2016	0.2239**	0.0631	0.3860**	0.1592	−0.0615	−0.1116*
	(0.1088)	(0.0834)	(0.1559)	(0.1143)	(0.0586)	(0.0658)
Relative emp. ratio	0.7538***	0.2546	1.1350***	0.4824*	0.3027	−0.3172
	(0.2004)	(0.1888)	(0.2733)	(0.2613)	(0.2536)	(0.3015)
Bartik * rel. emp. ratio	0.2803	1.3969	0.5905	2.4104	−2.1235	0.7927
	(1.5134)	(1.1881)	(1.9509)	(1.6175)	(1.3496)	(1.0188)
Bartik wage, 1999–2016	0.9494**	1.5577***	1.3576*	1.9275**	−0.2013	0.7933*
	(0.4624)	(0.4757)	(0.7515)	(0.7627)	(0.4472)	(0.4204)
Observations	371	383	371	383	371	383

Table 15B Area Characteristics that Predict Changes in CZ-Level and CBSA-Level Annual Earnings, between 2000 and 2017, by Race and Ethnicity

Characteristic	*Black residents*		*Hispanic residents*		*White residents*	
	CZ	CBSA	CZ	CBSA	CZ	CBSA
Black pop share	−0.3927**	−0.3133*	−0.1114	−0.2375	−0.2861***	−0.2922***
	(0.1926)	(0.1595)	(0.1926)	(0.1551)	(0.0530)	(0.0552)
Hispanic pop share	0.1199	−0.0023	0.1843*	−0.0218	−0.1071*	−0.2584***
	(0.1974)	(0.2039)	(0.1037)	(0.0949)	(0.0547)	(0.0552)
BA+ pop share	0.3440	0.1196	0.4890	0.4079**	0.1325	0.1424
	(0.3657)	(0.2137)	(0.3331)	(0.1793)	(0.1256)	(0.0871)
Bartik shock, 1999–2016	0.1305	0.0786	0.0812	−0.1194	0.1688*	0.0536
	(0.2893)	(0.2269)	(0.2930)	(0.2001)	(0.0916)	(0.0803)
Relative emp. ratio	0.4291	0.3570	0.7060	0.4848	0.6611***	0.1739
	(0.3644)	(0.4642)	(0.4887)	(0.3074)	(0.1839)	(0.2474)
Bartik * rel. emp. ratio	−0.1159	−0.0769	−0.5197	−1.5030	−0.1803	0.9447
	(2.3323)	(2.9763)	(3.3644)	(1.3907)	(1.4971)	(1.6547)
Bartik wage, 1999–2016	−1.5001	2.6765*	−1.4022	2.0632	0.9151**	1.2692**
	(2.0905)	(1.5624)	(1.8811)	(1.5758)	(0.4446)	(0.5196)
Observations	239	256	246	242	371	383

NOTE: Each column represents a separate regression with the outcome of the change in real annual median earnings, as previously described in the text, for either commuting zones (CZs) or metro areas (CBSAs) between 2000 and 2015–2019 (abbreviated as 2017), for a different group of CZ residents aged 25–64. All explanatory variables are measured as of 2000 unless otherwise noted; see text for descriptions. All regressions also include the additional variables shown in Table 12 even though these estimates are not shown. Standard errors robust to heteroskedasticity appear below coefficient estimates. ***, **, * imply p-values less than 0.01, 0.05, and 0.10, respectively.

Put differently, the availability of jobs may be more pressing a concern for economic revitalization in relatively rural areas, while the availability of higher-wage jobs may be more important in labor markets anchored by cities.

6. CASE STUDY NARRATIVES: A THEMATIC APPROACH

We conducted several case studies to provide historical context and, in some cases, deliberate strategies adopted by communities in their response to economic changes from 2000 onward. Primarily using a narrative lens, these case studies underscore how qualitative research can bring sociohistorical nuances to complement quantitative research and yield a more complete portrait of comparative economic trends (Yin 2009). Although we summarize the methods and findings in this section, the individual case studies themselves are available upon request.

Case Study Methodology

The specific community cases we cover are meant to highlight the diversity of the communities in our sample as well as illustrate the large variation across economic outcomes. We did, however, impose some additional selection criteria to focus on communities that are of high policy interest because of economic changes in recent decades. We began by selecting communities with a population under 500,000, that were east of the Mississippi River, and that did not contain a major land grant university or state capital.[23] Then, utilizing the rich dataset created out of this project, we selected paired cases based on the nearest five neighbor geographies according to socioeconomic characteristics in the year 2000. We determine neighbors by use of the Mahalanobis distance metric, a generalization of Cartesian distance that accounts for different scaling and correlation among multiple variables or characteristics. The characteristics we use for this purpose include: 1) log population; 2) Black share of the population; 3) Hispanic share of the population; 4) share of the population with at least a bachelor's degree; 5) shares of the population in age groups of 25–34, 35–44, and 45–54 (relative to the total population of aged 25–64); 6) a measure of the area's employment rate relative to the national employment rate, adjusting demographics between the two geographies to make them equal; 7) predicted employment growth between 1999 and 2016, based on the area's industry mix in 1999; and 8) predicted wage growth between 1999 and 2016, based on the area's industry mix in 1999.

[23] Unlike the quantitative analysis above, for the case studies we focus on CBSAs, as their more compact geographic scope makes it easier to investigate the importance of political and civic factors in an area's relative economic success.

To analyze our cases, we utilize qualitative comparative analysis (QCA). This cross-case method of analysis enables us to address questions of comparative historical development by exploring the relationship between conditions and outcomes (Ragin 1987). QCA can suggest multiple causal pathways to an outcome and allows for causal asymmetry (when specific factors explain success, their absence does not mean there will be failure); it is also well-suited for a moderate number of cases (Mello 2021). QCA thus complements the earlier quantitative analysis.

We selected the following cases for inclusion in this study:

- Decatur, IL
- South Bend-Mishawaka, IN
- Hammond, LA
- Battle Creek, MI
- Kalamazoo, MI
- Muskegon, MI
- Niles-Benton Harbor, MI
- Hattiesburg, MS
- Lima, OH
- Mansfield, OH

The selected cases share many commonalities. Throughout the 1980s and 1990s, nearly all of these communities experienced employment growth, but at rates slower than the national average. Between 2000 and 2007, prior to the Great Recession, each of the Midwestern cases except for Kalamazoo experienced employment loss (Bureau of Economic Analysis 2019). Indeed, most of these communities were already experiencing decline or stagnation prior to the recession. Many were primarily former manufacturing hubs that saw substantial declines in employment as firms either offshored or consolidated into larger companies and then ceased operations in the local area. Consequently, it was not uncommon for several of these communities to have been left with a singular large employer that local stakeholders worked hard to retain. Additionally, they appear to have received relatively little local or state government intervention during and after the Great Recession (Hershbein and Stuart 2023b).

As with the quantitative analysis, we focus with these case studies on explaining trends in real earnings, for all residents, for those without a bachelor's degree, and for Black residents. Our analysis provides some clues for why certain communities exceeded expectations in wage growth overall and for less-educated residents, but our investigation is less conclusive regarding divergences in wage growth for Black residents. Causal factors other than what we were able to uncover in our case studies may be responsible. Although we cannot pinpoint all salient factors, the analysis extends our extant knowledge and provides a scaffold for further research.

Federal and State Spending

Among case communities that outperformed earnings growth expectations, there was a clear pattern of large federal and state investments in these labor markets. This spending occurred through two primary mechanisms: direct employment and indirect payments.

Battle Creek, MI, and the two communities in OH, Lima and Mansfield, demonstrate the importance of direct employment by the state and federal governments. Battle Creek has a large military presence between the Fort Custer Army National Guard Base, the Air National Guard Base, the Defense Logistics Agency at the Hart-Dole-Inouye Federal Center, and the VA hospital. Combined, these organizations employ over 4,500 people (Battle Creek Unlimited 2021), or roughly 8 percent of the entire labor force (Bureau of Labor Statistics 2023). Similarly, Mansfield is home to two prisons. Six percent of area residents work in the prisons or in private security (Goebel 2011). Lima contains the Joint Systems Manufacturing Center, a government-owned, contractor-operated facility that runs the Lima Army Tank Plant and buys parts from dozens of other supply companies nearby. In 2017, the factory received an order for over $1 billion for upgrades to Abrams tanks, with another $714 million order for additional upgrades in 2019. Between 2015 and 2018 General Dynamics received an additional $4.25 billion in orders from foreign allies, primarily for tanks and tank refurbishment, although not all the work went to the Lima Plant (Smith 2018). Nonetheless, employment levels at Joint Systems Manufacturing doubled between 2016 and 2018 (Cloud 2018) and were projected to reach nearly 1,000 in the years after the conclusion of our study period (Fellman 2019).

The earnings benefits to these places from direct government employment likely stem from three channels. First, the federal government jobs in these areas are subject to the General Schedule for wage determination, and this national average benchmark carries further in areas with relatively low costs of living, as in these case communities. Second, many of these government positions are also unionized, which tends to raise wages and annual earnings. Third, many government jobs are subject to explicit equal opportunity and sometimes affirmative action requirements in hiring, which have been shown to lead to better access to jobs for racial minorities (Miller 2017). Thus, expansions in state and federal government jobs in areas where the private sector has contracted can counter earnings (and some employment) losses.

Indirect payments from governments have also helped some communities outperform on earnings growth. These payments often followed a disaster or crisis and reflected allocation of discretionary funds rather than entitlements (see Hershbein and Stuart 2023b). For example, Hammond, LA, saw a population boom following Hurricane Katrina, with an influx of over 10,000 people between 2005 and 2008, enough for the population to increase by about one-tenth in just three years (Federal Reserve Bank of St. Louis 2023). Many of these migrants were climate refugees from areas hit by the hurricane (especially from New Orleans, an hour to the southeast), who were receiving FEMA emergency assistance funds. Likewise, Benton Harbor, MI, received more than $160 million from state and federal sources to rebuild the city following a series of riots that occurred in 2003 (Holcomb 2008). The community used these monies to both rebuild damaged properties and invest in new infrastructure, job training, and adult education. The infusion of cash into these communities thus acted as a form of fiscal stimulus in places otherwise facing economic distress.

Both channels likely spurred increases in local labor demand and supply, creating a ripple effect by boosting demand for various goods and services, further stimulating economic growth. Moreover, they also worked as a safety net for communities facing economic challenges, helping to stabilize consumer spending and allow workers to gain training for better jobs. These patterns suggest that the recently enacted pilot in the RECOMPETE Act (itself part of the CHIPS and Science Act of 2022), which is set to provide multiyear, flexible block grants to a small number of economically distressed communities throughout the country, could represent an innovative approach to accelerate earnings growth in places where it has been lacking. Studies of the program's effectiveness, for which we anticipate there will be several, may shed more light on how government grants can most effectively boost earnings for different groups of residents.

Local Champions

Another key factor in communities with higher-than-predicted earnings growth is the presence of community champions; that is, businesses, people, or philanthropic organizations that either invest in the community monetarily or persuade other stakeholders to do so.

In some cases, community foundations play this role. In Battle Creek, for instance, the W.K. Kellogg Foundation has been a major champion of the city, providing funding for countless economic development projects and philanthropic efforts. The foundation also works closely with Battle Creek Unlimited, the region's economic development organization. The

Richland County Foundation in Mansfield also contributes heavily to funding local projects, benefiting from a relatively large endowment built by a history and culture of business philanthropy. Mansfield also stands out because of the alignment of its philanthropic organizations, which have acted as a consortium to pool resources and make joint annual allocations to agreed-upon initiatives. This structure can magnify the impact of investments on economic growth due to scale effects and avoiding fragmentation from disparate, overlapping efforts.

Corporations can also serve as sources of investment in the community. In Niles-Benton Harbor, MI, the Whirlpool corporation, which is headquartered there, has over the past decade contributed tens of millions of dollars toward the initial development of the Golf Club at Harbor Shores and the larger resort of which it is part (Eliasohn 2007), in addition to investments totaling around $190 million toward its local operations between 2011 and the end of our study period (Moody 2017). Because the club and resort bring in significant tourism—it is a recurring site for the Senior PGA Championship—Whirlpool's investments, even for a business development, have created ancillary economic activity and jobs, some of which are filled by residents of nearby economically challenged neighborhoods (Bartik 2022b, 2022c).

Yet, the presence of deep-pocketed philanthropists, whether individual, nonprofit, or corporate, does not guarantee relative economic success, either. Kalamazoo, MI, for example, has strong philanthropic institutions from its having been the headquarters of the Upjohn pharmaceutical company and the current headquarters of the Fortune 500 company Stryker (medical devices), and it is also home to the nation's premier place-based scholarship program, the Kalamazoo Promise. However, the community underperformed relative to expectations and several of the other cases. Similarly, South Bend, IN, despite containing a major private research university, Notre Dame, hardly outperformed expected earnings growth.

Discussion

Many, but not all, communities that outperformed earnings expectations based on economic fundamentals benefited from external sources of funding and investment. Strong civic leadership also emerged as a theme in these communities, particularly in conjunction with local philanthropy.

Although our findings do not necessarily generalize beyond the communities studied, a drawback of the case study method, they point to the need to further study how direct government investment in jobs and infrastructure, especially in distressed places, can change the trajectory of earnings growth for residents. This may be especially important since the association between these investment factors and earnings growth was stronger for residents overall than for Black residents or residents without a bachelor's degree.

7. A DATABASE FOR UNDERSTANDING LOCAL LABOR MARKET SUCCESS

The analyses we have presented above, although illustrating several previously understudied trends and stylized facts about the economic success of different local labor markets, and how this success varies for different groups of residents, barely scratch the surface in terms of how the assembled data can help address key policy questions. For example, policymakers often wish to attract early-career workers and families to their communities, in part because this demographic group is associated with economic dynamism and broad demand for locally provided spillover services, from new housing to child care to restaurants. Because the full dataset we have compiled includes characteristics for 160 demographic cells, it is straightforward to focus on trends for 25–34-year-olds, or even 25–44-year-olds, comparing which communities have seen, for instance, faster earnings growth for these age groups versus growth in population shares but without earnings growth. Alternatively, with many communities increasingly interested in the equity of economic opportunity, policymakers may want to understand the trajectory profile of groups particularly disadvantaged in the labor market, such as Black males, and whether employment gains are being concomitantly met with hourly wage gains.

Moreover, we have produced, for each geography (CZ and CBSA), a set of the nearest five neighbor geographies based on similar characteristics in the year 2000 (the ones used in the regression analysis in Section 5).[24] We provide three different "donor sets" for these nearest neighbors: the entire United States, the Census Region (Northeast, Midwest, South, and West), and the Census Division (New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific). Thus, policymakers also can compare economic progress for their own area to peer communities, both nationally and regionally, and not just for their residents overall but for specific demographic groups.

We have shared the core data files we have used in the analyses in this report and the nearest neighbors file, along with documentation, in several formats through the freely accessible data repository openICPSR, operated by the University of Michigan.[25] Data analysts for local and state governments, economic development organizations, businesses, and other researchers

[24] To construct matched or nearest neighbors for the geographies, we use an approach called Mahalanobis matching, described more fully in the previous section. The basic idea is to find for each focal geography the closest other geographies based on similarity of a set of characteristics. The algorithm accounts for different scaling of the characteristics and their possibility of correlation.
[25] Available file formats include Stata, SAS, R Workspace, and comma separated value for other software packages.

can access and use the data to address the questions above or many others of interest. Although our analyses have focused on areas with at least 100,000 residents, the data files contain smaller areas as well.

8. CONCLUSION

In this report, we revisit the relative economic success over the past two decades of different local labor markets throughout the United States, for different groups of residents. Constructing a new set of economic indicators that account for demographic and cost-of-living differences, we examine how and why some areas—both commuting zones and metropolitan areas—have performed better than others. Our analysis yields several take-away conclusions:

1) Communities show wide disparities in their labor market success over the past 20 years, both overall and for different groups of residents.
2) Local labor market success often varies widely across different indicators; areas that saw large gains in employment rates, for example, often did not see large gains in hourly wages. This points to the importance of considering multiple indicators when evaluating success.
3) Although earnings index growth is moderately correlated across different education and racial/ethnic groups, it is common for an area that shows strong growth for one group to not show strong growth for other groups.
4) Although we find some expected patterns in our labor market success measures—some large high-tech cities do well overall and across different groups of residents—many unsung areas also show quite robust and broad-based success. Moreover, some

of the commonly touted areas that show overall success fare poorly in their trend measures for individuals of color or those without a bachelor's degree.

5) Local labor markets exhibit greater variation in labor market outcome trends for persons from economically disadvantaged groups, such as residents without a bachelor's degree and Black residents, than economically advantaged groups. Put differently, place matters more for the economically vulnerable.

6) Labor market forces and demographic factors both shape trends in local labor market outcomes. A greater local concentration of industries that grow faster nationally improves labor market trends, particularly for residents without a bachelor's degree.

7) Trends in labor market outcomes also tend to be worse in areas with a higher share of the population that is Black. This pattern is not due to other associated demographic composition factors along age or education lines, or even economic fundamentals, but rather reflects some other labor demand-side or supply-side influence on labor market outcome trends that is hard to pinpoint.[26]

8) On the other hand, trends in labor market outcomes for residents with a bachelor's degree tend to be better in areas with a higher initial share of highly educated residents.

9) Our case studies, which examine initially similar, midsize local labor markets, suggest other important channels, particularly that of direct government investment as an employer or provider of funds and that of local civic, business, or institutional leadership. Although some of these factors are hard to replicate, they do suggest a

[26] Some might argue that this is evidence in favor of a structural racism explanation. Although this is certainly a possible hypothesis, it is not very specific in terms of proximate explanations. A few specific channels that deserve further investigation include differential investment by state policymakers, differential credit/capital access, and environmental health.

role for targeted government investment policies, such as the RECOMPETE Act, and the importance of keeping leaders from longstanding community institutions.

More broadly, however, these results represent only a beginning to what can be learned from the new data assembled for this project. Researchers from academia, government, and business can explore other local, regional, or national determinants of the overall trends we have examined, from key employers entering (or leaving) the area to changes in state tax policy to exposure to international trade shocks. Or researchers can zoom in on narrower demographic groups, such as young Black males or less-educated residents nearing retirement age, to both observe these groups' trends and what might explain them. Policymakers can use the data to compare their own area's performance, both overall and for different groups, to initially similar peer areas (these "neighbors" are also provided in the data).

To facilitate these uses, we have made the data publicly available through the openICPSR data archive. Furthermore, we may be able to update these data in the future. When sufficient years of data are available, for example, we intend to add a post-pandemic period, allowing investigation into how COVID-19 affected long-term labor market trajectories across places and for different groups of residents.

In summary, labor market outcomes for different groups vary enormously across local labor markets. It may be an exaggeration to say that "all labor markets are local," but it is not far from the truth. Our knowledge about local labor market success hinges on understanding who is making progress relative to what is possible, and we have argued that this requires making apples-to-apples comparisons, accounting for differences in demographic composition and local prices. Our hope is that this report and the data we share will make it easier for others to make these comparisons, and understand how economic events—and public policy—affect both local and national labor market outcomes.

APPENDIX A

Detailed Data Calculations: Prices and Wages

A.1 Housing Price Calculations and Local Price Calculations

We construct indices for relative housing prices using reported rents as captured in the 2000 Census and in the ACS. Specifically, for each geography (nation, CZ, or CBSA) and relevant time period (2000, 2005–2007, 2015–2019), we calculate average (gross) rents for both two-bedroom and three-bedroom apartments.[27] We then create a weighted average of these two rent measures, where the weights reflect the *national* share of each type and sum to 1 (we thus implicitly ignore other rental unit types). For each subnational geography, we divide this rent measure by the national equivalent to create a ratio reflecting the area's relative housing price.

We then subtract 1 from this relative housing price ratio to get each area's differential housing price, as a proportion of national housing prices in the nation. We multiply this differential by 0.5, and then add back in the 1. The resulting ratio is our estimated local price differential.

The 0.5 weight on relative housing prices in computing overall local prices is based on Aten (2006). She calculates local housing price differentials and local overall price differentials for 38 areas using BLS data. Her regression of the latter on the former yields a coefficient of 0.501 with a standard error of (0.029). This 0.50 coefficient is greater than the weight of 0.32 that overall shelter has in BLS's Consumer Price Index, but this greater weight likely reflects correlation of housing prices with the prices of other goods and services purchased locally.

[27] Since we make these calculations from the microdata, we employ PUMA-to-CZ (or PUMA-to-CBSA) crosswalks provided by the Missouri Census Data Center's Geocorr program (versions 2000 and 2018) to construct statistics at the relevant geographies. See https://mcdc.missouri.edu/applications/geocorr.html.

Other researchers have used similar procedures. Moretti (2013) and McHenry and McInerny (2014) both use a slightly simpler method of pooling two-bedroom and three-bedroom rents and taking the local-to-national ratio, without calculating two-bedroom and three-bedroom rents separately. The correlation across 371 CZs between these simpler calculations and our measures is 0.99. McHenry and McInerney use a housing weight of around 0.40, derived from the housing weight in the CPS. Moretti uses a weight of 0.62, derived from his own regression of changes in local overall prices on changes in local housing prices. McHenry and McInerney's procedure may underestimate local price differentials, as it ignores spillover effects of housing prices on other local prices. Moretti's approach may in turn overstate the long-run influence of housing prices on local overall prices, as demand shocks that increase housing prices will also increase local real wages. We view our chosen weight of 0.50 as a reasonable compromise.

A.2 Wage Calculations

We determine median annual earnings and hourly wage rates by area from Census and ACS data. We focus on employee workers and exclude those with self-employment income. Wage and salary earnings are directly reported, although we exclude from our calculations individuals for whom earnings are imputed. We calculate hourly wage rates as wage and salary earnings divided by annual hours worked. Annual hours worked, in turn, are derived by multiplying usual hours worked per week by the number of weeks worked in the past calendar year (2000 Census) or 12 months (ACS). As the number of weeks worked is available only categorically in the ACS, we use the midpoint of the reported weeks-worked interval. To reduce outliers, we also exclude from the hourly wage calculations individuals who report working fewer than 14 weeks over the past 12 months or who report fewer than 11 usual hours worked per week. These rules help reduce measurement error and division bias (Baum-Snow and Neal 2009; Perry, Thomason, and Bernhardt 2016).

APPENDIX B

Detailed Data Calculations: Shift Share Measures

B.1 Shift-Share "Bartik Shock" Predicted Employment

To create predicted job growth ("Bartik shocks") for overall employment for each local labor market (commuting zone [CZ] or metro area [CBSA]), we use a desuppressed version of the Census Bureau's County Business Patterns employment data, called WholeData, maintained by the W.E. Upjohn Institute for Employment Research (Bartik et al. 2018). These data provide near-exact employment counts for six-digit NAICS industries for each U.S. county for the years 1998–2016. For each area (CZ or CBSA), we calculate the share of employment in the base period (either 1999 or 2006) in each detailed industry—the local industry mix of employment. We also calculate the national percentage growth in each industry between 1999 and 2016, or 1999 and 2006, or 2006 and 2016. We then multiply these industry-level national growth rates by each area's industry share and sum these products across industries for each area to yield a predicted growth rate for each area. This prediction can be interpreted as the change in employment in the area that would be expected due to national demand trends applied to an area's export-base industries (Bartik 1991).

We use the year 1999 rather than the year 2000 as the baseline because our main labor market measures from the 2000 Census refer to earnings in calendar year 1999 and employment status as of April 1 of 2000, so 1999 is a closer match. We use the year 2016 as an endpoint (rather than 2017, the midpoint of 2015–2019) because it is the last year available in WholeData.[28] Moreover, the ACS data on wages and earnings are lagged over the previous 12

[28] Starting in 2017, the Census Bureau changed the release format of County Business Patterns, making the desuppression algorithm WholeData uses infeasible.

months, so the 2015–2019 waves capture earnings from 2014–2018. Similarly, we use 2006 as the midpoint of the 2005–2007 period.

Mathematically, we construct the demand shock for area *j* and base period *t* as:

$$Bartik_{j,t}^{IV} = \sum_i \frac{E_{ijt_0}}{E_{jt_0}} \left[\frac{E_{it_1} - E_{it_0}}{E_{it_0}}\right],$$

where E_{it_0} is national employment in detailed industry *i* in base period t_0, E_{it_1} is national employment in detailed industry *i* in end period t_1, E_{ijt_0} is employment in local area *j* in detailed industry *i* in base period t_0, and E_{jt_0} is total employment in local area *j* in base period t_0. (The ratio of the last two is thus the share of employment in area *j* that is in detailed industry *i*.)

B.2 Shift-Share "Bartik Wage Shock" Industry Wage Premia

B.2.1 National wage premia by time and industry

We desire demographically-adjusted wage "premia" for each of 119 industries and three time periods (1999, 2006, and 2016). We work with 119 industries, rather than the approximately 1,000 six-digit NAICS industries used in Appendix B.1, because we can consistently identify only this number of industries in the 2000 Census and ACS, and we need to use the Census and ACS for demographic adjustment. The wage premia address the question of how much larger or smaller is the average hourly wage in an industry than the industry's demographic composition would lead one to expect. We construct the national wage premia in four steps.

First, we construct real ($2019) median hourly wages at the *national* level, for each of the three time periods and for each of the 160 demographic cells. Second, for each industry and time period, we calculate the share of the wage sample in each of the 160 demographic cells. Third, we combine (multiply and then sum across cells) the results in the first and second steps to calculate the weighted mean of the median national wage rates for each of the 119 industries and three time periods. These results provide the national industry hourly wage under the assumption that every demographic group in that industry were paid its national median hourly wage. (Put differently, it predicts the industry hourly wage purely from the industry's demographic composition.) Fourth, we calculate the ratio of the actual industry national median hourly wage to the constructed measure from the third step. These ratios, or wage premia, tell us whether the hourly wage is above or below what we would expect from the industry's demographic composition.

B.2.2 Constructing "Bartik wage shock" wage premia

We assign the 119 industry wage premia as constructed above, separately for each time period, to the full set of more detailed industries in WholeData. Since the 119 industries are aggregates of the detailed set of industries, this approximation, although not ideal, should be serviceable.

We build the wage shock instrument in three parts:

[A] $$Bartik_{j,t_0}^{IV_{wage}} = \sum_i \frac{E_{ijt_0}}{E_{jt_0}} \left[W_{it_0}\right],$$

[B] $$Bartik_{j,t_1}^{IV_{wage}} = \sum_i E_{ijt_0} * \frac{E_{it_1}}{E_{it_0}} * \left[\sum_i E_{ijt_0} * \frac{E_{it_1}}{E_{it_0}}\right]^{-1} * \left[W_{it_1}\right],$$

[C] $$Bartik_{j,t_1-t_0}^{IV_{wage}} = Bartik_{j,t_1}^{IV_{wage}} - Bartik_{j,t_0}^{IV_{wage}}.$$

Line A is the predicted hourly wage premium in area *j* in the base period. It is the local area's industry-weighted average of the national, industry-level real hourly wage premia, W_{it_0}, as calculated in Appendix B.2.1. Weighting these industry-specific wage premia by local industry shares, as in Line A, results in the variation across places being driven solely by the area's industry mix, as captured by $\frac{E_{ijt_0}}{E_{jt_0}}$ across industries for each area *j*. Intuitively, $Bartik_{j,t_0}^{IV_{wage}}$ can be seen as the predicted percentage deviation of wages in the area from the overall national average due to 1) the area's industry mix; and 2) each industry's deviation from typical expected wages.

Line B is the predicted industry wage premium in area *j* in the later period; this calculation is more involved. The first two terms after the initial summation term include the base period employment in area *j* for industry *i*, E_{ijt_0}, multiplied by the national growth in that industry, $\frac{E_{it_1}}{E_{it_0}}$. This yields the predicted level of employment in industry *i* in area *j* in the later period if baseline employment in industry *i* and area *j* grew at the national rate. The term in the square brackets repeats this expression but sums across industries and, because of the −1 exponent, effectively shows up in the denominator. This term is the predicted *total* employment in area *j* in the later period if each industry's employment grew at the national rate. The last term is the national, real hourly wage premium for the industry in the later period. Thus, for the whole line, we again calculate a weighted average of the national real hourly wage premium for each industry, and we normalize each industry's predicted employment growth by the area's total predicted employment growth so that weights sum to 1. This approach simulates what area *j*'s industry mix would be in the later period if all of its industries grew at their national rates, and then applies this simulated industry mix as a set of weights for each industry-specific wage premium to produce a total, end-period wage premium for the area.

Line C simply subtracts Line A from Line B. Because Line A is area *j*'s predicted *base period* wage premium from its industry mix and national industry wage premia, and Line B is area *j*'s predicted *final period* wage premium from its predicted industry mix and national industry wage premia, Line C is the *change* in the predicted wage premia in area *j* and is a function of the area's base period industrial mix, national industry growth trends, and changes in industry wage premia. The expression in Line C, $Bartik_{j,t_1-t_0}^{IV_{wage}}$, is what we use in our explanatory regressions as the "Bartik wage shock."

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