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Abstract

This paper studies how U.S. local labor markets respond to employment losses after recessions. Following each recession between 1973 and 2009, we find that areas that lose more jobs during the recession experience persistent relative declines in employment and population. Most importantly and contrary to prior work, these local labor markets also experience persistent decreases in the employment-population ratio and per capita earnings. Our results imply that limited population responses result in longer-lasting consequences for local labor markets than previously thought, and that recessions are followed by persistent reallocation of employment across space.

JEL Classification Codes: J21, J61, R23

Keywords: local labor markets, recessions, employment rates, migration

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1 Introduction

Recessions are a perennial feature of market economies. Since at least 1950, the U.S. unemployment rate has tended to recover gradually after contractions (e.g., Dupraz, Nakamura and Steins-son, 2020; Hall and Kudlyak, 2020), which raises the possibility that recessions have only modest long-run effects on the nationwide labor market. However, as recession severity can vary considerably across geographies, recessions could nonetheless have persistent consequences for local labor markets. The importance of understanding whether local areas also recover fully from recessions is underscored by a growing literature showing that local factors shape a range of outcomes—such as intergenerational mobility (Chetty and Hendren, 2018a,b), health (Finkelstein, Gentzkow and Williams, 2021), and voting (Charles and Jr., 2013; Autor et al., 2020).

A series of influential studies suggest that local labor markets do recover completely from most recessions. Seminal work by Blanchard and Katz (1992, hereafter BK) finds that population adjusts quickly to changes in local labor demand, generating complete recovery of state employment rates within ten years. Using additional years of data and a different source of identification to estimate the BK model, Dao, Furceri and Loungani (2017) find that population is less responsive in the short run, but their estimates also imply full recovery of employment rates after labor demand shifts. Yagan (2019) applies the BK methodology to study recessions and finds rapid recovery following the 1980–1982 and 1990–1991 recessions, but slower recovery from the more severe Great Recession. Monras (2020) uses a different empirical strategy, but also finds lasting effects on local areas after the Great Recession. One interpretation of this evidence is that recessions must be especially severe to generate persistent impacts on local labor markets. The accuracy of this interpretation has broad implications for our understanding of labor markets, economic opportunities available to workers and their children, and appropriate policy responses.

This paper studies the response of U.S. local labor markets to employment losses that emerged during each recession between 1973 and 2009.\footnote{These recessions took place in 1973–1975, 1980–1982 (we pool the very short recession in 1980 with the longer one in 1981–1982), 1990–1991, 2001, and 2007–2009.} Specifically, we study how employment, popula-
tion, and earnings evolve in local areas (metropolitan areas and commuting zones) where national recessions are more versus less severe. We draw upon multiple data sources, including those from the Bureau of Economic Analysis and the Census Bureau, to create annual panels of longitudinally-harmonized geographic areas stretching over five decades. We estimate regression models that relate the evolution of local economic activity to sudden employment changes that arise during recessions, while controlling flexibly for changes in economic conditions at the regional level, as well as pre-recession population trends. This empirical strategy allows us to examine the extent to which local labor markets with larger employment losses during recessions recover relative to areas with smaller employment losses.

We find that declines in employment that emerge during recessions are extremely persistent. Across the five recessions that we study, a 10 percent decrease in metropolitan area employment during the recession, roughly the 90–10 percentile gap across areas for the Great Recession, on average leads to a 12 percent decrease in employment 7–9 years after the recession trough. The sudden decreases in employment that occur during recessions are not driven by differential pre-trends beforehand.

The consequences of these local employment declines depend on the extent of population adjustment. We find that metropolitan areas with larger employment losses experience population declines that begin during recessions and continue to grow for several years after the recession trough. The post-recession decrease in population is persistent, but smaller than the decrease in employment. Due to this limited population response, local employment losses are followed by persistently lower employment-population ratios. On average, a 10 percent decrease in employment during a recession leads to a 6.6 percent (4 percentage point) decrease in the employment-population ratio. The change in the employment-population ratio accounts for about 54 percent of the decline in local area employment 7–9 years after the recession trough, with the decline in population explaining the remaining 46 percent. Moreover, these relative declines in employment-population ratios persist until 2019. Local employment losses during recessions also are followed by lasting decreases in per capita earnings.
Our findings are consistent with local labor markets that experience larger employment losses during recessions facing a persistent downward shift in labor demand in the presence of a labor supply curve that is less than perfectly elastic but more elastic than population. Moreover, the fact that the vast majority of employment losses occur during recessions suggests that these results reflect persistent consequences of labor market shifts that occur primarily during recessions, as opposed to a series of shifts taking place throughout the post-recession period. Consistent with this interpretation, we also show that our findings are not driven by secular changes in local economic activity that are correlated with pre-recession industrial structure.

To further contextualize our results and corroborate our interpretation, we conduct several supplementary analyses. First, we find that relative declines in local employment are widespread across all sectors. Second, we use IRS data to show that the decline in population after the 2001 and 2007–2009 recessions arises from lower in-migration to local areas that experience larger employment losses. Out-migration actually falls after recessions in negatively affected areas. Third, we use individual-level data from the decennial census and American Community Survey to show that annual earnings declines tend to be more severe at the bottom and middle of the distribution. On average, about three-quarters of the medium-term decline in annual earnings for those who remain employed arises from a reduction in hourly wages. Finally, using two complementary approaches, we present suggestive evidence that a change in the composition of residents due to selective migration does not account for most of the decline in local employment-population ratios or average earnings. Instead, the declines appear to stem mainly from lasting impacts on individuals, consistent with evidence on the effects of job displacement (e.g., Jacobson, LaLonde and Sullivan, 1993; Davis and von Wachter, 2011; Lachowska, Mas and Woodbury, 2020; Schmieder, von Wachter and Heining, 2020).

Our results contrast with prior influential papers. In particular, Blanchard and Katz (1992) find that the unemployment rate, the labor force participation rate, and wages return to trend within ten years of a decline in local employment. Dao, Furceri and Loungani (2017) estimate convergence that is slower, but still ultimately complete. In both of these papers, recovery begins about two
years after employment decline. Using empirically-relevant Monte Carlo simulations, we show that finite sample bias arising from a limited number of time series observations leads VARs estimated in prior work to incorrectly imply convergence in cases where a decline in employment leads to permanent reductions in the employment-population ratio. This finite sample bias, which would be of first-order importance even if researchers had access to 100 years of data, explains the difference in our results from those based on the BK VAR model.

The key contribution of this paper is evidence over a 50-year period on the response of local labor markets to employment losses that emerged during recessions. Our focus on recessions is motivated by two considerations. First, recessions have attracted substantial attention from researchers, policymakers, and the public. Second, as we show, recessions lead to sudden employment losses that break from pre-existing trends, allowing us to generate transparent evidence on the evolution of local economic activity with flexible regression models. Our results show that local employment losses during recessions are followed by lasting shifts in the spatial distribution of employment and population. The results also show that relative reductions in employment rates and earnings last longer than previously thought. Moreover, post-recession changes in local labor market outcomes are remarkably similar over the past five decades, which underscores the extent to which persistent local labor market disruption is a general feature of the U.S. economy.

Our work complements recent research that uses local labor market variation to understand the consequences of recessions. Yagan (2019) uses tax data to provide evidence that people living in areas severely affected by the Great Recession experienced enduring employment and earnings losses. We differ from Yagan (2019) by focusing on how recessions affect local labor markets, as opposed to individuals, and by examining a larger number of recessions. Monras (2020) provides empirical evidence that reduced in-migration accounts for essentially all of the population decline in areas hit harder by the Great Recession and develops a structural model to rationalize this fact. Our findings on in-migration are qualitatively similar. We differ from Monras (2020) in

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Our empirical strategy and examination of more recessions and more outcomes.

Our work also complements several other studies that examine how local labor demand shifts, such as a change in manufacturing jobs, affect earnings, employment, population, and labor force participation (e.g., Bound and Holzer, 2000; Freedman, 2017; Amior and Manning, 2018; Beaudry, Green and Sand, 2018; Garin, 2019; Gathmann, Helm and Schönberg, 2020; Notowidigdo, 2020; Cajner, Coglianese and Montes, 2021). We provide new evidence by combining annual data—which directly reveal local labor market dynamics—and a research design that studies local employment shifts over a 50-year period. Additional evidence is particularly valuable because of the disagreement in the literature over whether shifts in local labor demand have persistent effects on wages and employment, and how, when, and why these relationships may have changed (Bartik, 1993, 2015; Austin, Glaeser and Summers, 2018).3

Amior and Manning (2018) also show that incomplete adjustment of population to local employment shifts can generate persistent gaps in employment-population ratios. We differ in our use of sudden shifts in local employment that arise during recessions and our use of annual data, as compared to their analysis of predicted employment changes based on industrial structure (Bartik, 1991) using decadal data. Based on instrumental variable estimates of how employment responds to population and how population responds to employment, the model in Amior and Manning (2018) implies highly persistent labor demand innovations. In our setting, this would imply that areas that experience more severe recessions face additional negative labor demand shocks after recessions. Our estimates reveal that the vast majority of local employment losses occur during recessions, and our results are robust to controlling for pre-recession local industry shares; both findings suggest that persistent local labor market declines do not arise in our setting because labor demand innovations are strongly correlated over time. Instead, our results suggest that the effects of specific labor demand disruptions that arise during recessions are persistent.

We emphasize that our finding of persistent local labor market declines is not inconsistent with

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3Greenstone and Looney (2010) and Stuart (2022) provide evidence that recessions are followed by persistent declines in per capita earnings at the county level; our analysis goes considerably further, by examining a larger range of outcomes, other levels of geography, additional recessions, and proximate mechanisms.
aggregate economic recovery. The cross-sectional identifying variation we use identifies relative
differences in the evolution of local labor market outcomes between areas that experience more or
less severe employment losses during recessions.\(^4\) A persistent relative decline does not imply that
an area fails to recover in an absolute sense, but rather that a gap remains between that area and
one that experienced a less severe recession. These relative differences most directly shed light on
the distributional consequences of recessions and the efficiency costs associated with incomplete
local labor market adjustments.

2 Conceptual Framework

To guide our empirical analysis, we describe how local labor markets might evolve after recessions.
This discussion informs our empirical strategy and the interpretation of our results.

The basic unit of analysis is a local labor market. For each local area, we assume that labor
demand is downward sloping in the wage, as would arise under a diminishing marginal product
of labor or a downward sloping output demand curve. We further assume that local labor supply
and population are distinct and that each is weakly increasing in the wage. The separation of
labor supply and population allows the employment-population ratio to be below one. The most
natural situation is that the elasticity of labor supply is larger than the elasticity of population. For
example, this would arise when an increase in the wage draws existing residents into the labor
force and attracts new residents to the area.\(^5\)

Panel A of Figure 1 illustrates this framework graphically. The equilibrium wage and em-
ployment levels are determined by the intersection of the labor demand and supply curves. The
equilibrium population level is determined by the intersection of the equilibrium wage level and
the population curve. The employment-population ratio is also determined in equilibrium.

\(^4\)Other papers studying local labor markets also identify relative differences (e.g., Blanchard and Katz, 1992;
Autor, Dorn and Hanson, 2013; Amior and Manning, 2018).

\(^5\)There are several possible explanations for why the labor supply elasticity could exceed the population elasticity.
For example, working-age individuals might be more mobile than other individuals (such as retirees). Working-age
individuals also could care more about employment opportunities than individuals that are not working. Finally,
individuals might adjust their labor supply without moving, possibly by dropping out of the labor force when wages
fall below their reservation level.
Consider a local area that experiences a decline in employment during a recession. Over a short horizon of 2–3 years, the most natural catalyst of this fall in employment is a downward shift in labor demand. The fall in demand could stem from many possible sources, such as an increase in interest rates or oil prices or a decline in consumer sentiment. Employment will fall during a recession, as will wages and employment rates if labor supply and population are less than perfectly elastic in the short run.

After the recession, the local labor market could recover to varying degrees. We describe three cases.

First, the local labor market could return to its pre-recession values of employment, population, the employment-population ratio, and wages. Complete recovery would happen if the downward shift in labor demand is temporary and there is no shift in labor supply, as shown in panel B of Figure 1. For example, this pattern would arise if firms temporarily laid off workers or reduced their hours and there was no change in the non-wage determinants of labor supply and population (such as quality of life).

Second, the local labor market could experience persistent decreases in employment and population but little change in the employment-population ratio and wages, as shown in panel C of Figure 1. This could arise in the presence of a persistent shift in labor demand as long as the supplies of both labor and population to a local area are highly elastic. A persistent downward shift in labor demand will decrease local employment and population, but if individuals’ labor supply and migration choices are extremely sensitive to local job opportunities, then a combination of labor force exits, higher out-migration, and lower in-migration could re-equilibrate the local labor market at near its original employment-population ratio and wage level. The results in Blanchard and Katz (1992) are consistent with this scenario.

Third, the local labor market could experience persistent decreases in employment, population, the employment-population ratio, and wages, as shown in panel D of Figure 1. This would occur, for example, if the labor demand shift is persistent and the supplies of labor and population to a
local area are both relatively inelastic.\textsuperscript{6} In this case, the levels of employment, population, and wages would generally remain depressed. If labor supply is more responsive than population, then the employment-population ratio would remain depressed as well. A similar pattern would arise if the initial shift in labor demand is temporary but leads to subsequent downward shifts in labor demand (e.g., as shocks are transmitted through input-output linkages).

Why might the decline in employment during recessions be associated with a persistent shift in labor demand? Recessions could spur employers to change their production process so that routine tasks are performed by capital instead of labor (Jaimovich and Siu, 2015; Hershbein and Kahn, 2018). Recessions also could lead to establishment deaths (Foster, Grim and Haltiwanger, 2016), and the presence of obsolete durable capital could make it more costly for new businesses to occupy the same space.\textsuperscript{7}

Heterogeneous responses across types of workers also could contribute to changes in wages and employment rates. For example, if high-income workers are more likely to leave an area in response to a decrease in local employment (Bound and Holzer, 2000; Wozniak, 2010; Notowidigdo, 2020), then average wages might fall simply because of a change in worker composition. If younger workers are more likely to leave an area in response to a recession shock (Molloy, Smith and Wozniak, 2011)—or are less likely to move in—then the employment-population ratio might fall.

Because economic theory allows for the possibility that local labor markets recover from recessions to varying degrees, our goal is to estimate empirical relationships in a flexible manner. We now turn to describing the data and empirical strategy used in the rest of the paper.

\textsuperscript{6}Many spatial equilibrium models in the tradition of Rosen (1979) and Roback (1982) assume that individuals are perfectly mobile across areas. However, several empirical studies provide evidence of mobility frictions (e.g., Molloy, Smith and Wozniak, 2011, 2014; Bartik, 2018; Zabek, 2019; Ransom, 2021).

\textsuperscript{7}The possibility of a persistent decline in local labor demand relates to the relative importance of agglomeration and locational fundamentals as determinants of economic geography. Davis and Weinstein (2002, 2008) find striking evidence of a recovery in Japanese city population and manufacturing employment following Allied bombings in World War II. These results suggest that rationalizing a persistent decline in local labor demand would require that fundamentals change during recessions. This might seem surprising, but the presence of adjustment costs could diminish firms’ responses to secular changes, and firms might pay these adjustment costs during recessions (Foote, 1998). Moreover, there is some disagreement about the relative importance of fundamentals and agglomeration (e.g., Bosker et al., 2007; Miguel and Roland, 2011; Michaels and Rauch, 2018).
3 Data and Empirical Strategy

3.1 Data

We compile several public-use data sets to measure local economic activity. These data sets are constructed by government agencies using administrative data. Employment is available from the Bureau of Economic Analysis Regional Economic Accounts (BEAR), Census County Business Patterns (CBP), and Quarterly Census of Employment and Wages (QCEW).\(^8\) BEAR and CBP data are available starting in 1969, while QCEW data are available from 1975 onward. BEAR data also contain aggregate earnings.\(^9\) We use the National Cancer Institute’s Surveillance, Epidemiology, and End Results (SEER) data for annual population estimates, which are available by sex, race, and age. To measure in- and out-migration, we use the Internal Revenue Service Statistics of Income (SOI) data.\(^10\) Finally, we use tabulations and microdata from the decennial census and the American Community Survey (ACS) to examine the earnings distribution and composition changes.\(^11\)

With the exceptions of the decennial census and ACS microdata, all of the data sets are available at the county level. The census and ACS are available at the Public Use Microdata Area (PUMA) level, which we map to other geographies using crosswalks available from the Geocorr program of the Missouri Census Data Center. Consequently, we can examine changes in eco-

\(^8\)Because employment counts are often suppressed for small counties and industries in CBP data, we adopt the imputation procedure of Holmes and Stevens (2002) when necessary. Details are in the Data Appendix. Results from this approach agree closely with WholeData, which uses a linear programming algorithm to recover suppressed employment estimates (Bartik et al., 2019).

\(^9\)More specifically, BEAR data contain earnings by both place of residence and place of work. Since wage and salary employment is available only by place of work, we use the corresponding earnings measure and define earnings to be wages, salaries, and supplements (benefits). As discussed more below, our results are similar when measuring earnings by place of work or place of residence.

\(^10\)SOI data are available starting in the 1990s. Although they capture moves only for tax filers, SOI data are considered a high-quality source for point-to-point migration flows and have been used in several papers (e.g., Kaplan and Schulhofer-Wohl, 2012, 2017; Wilson, Forthcoming). We use a version of these data compiled by Janine Billadello of Baruch College’s Geospatial Data Lab (Billadello, 2018).

\(^11\)We use versions of these tabular and microdata from NHGIS and IPUMS, respectively (Manson et al., 2019; Ruggles et al., 2019). The Data Appendix describes the processing of these data and how we link individuals to our geographies of interest.
nomic activity for metropolitan areas and commuting zones.\textsuperscript{12} Metropolitan areas and commuting zones are commonly used to approximate local labor markets, although there is some disagreement as to which provides the better approximation (Foote, Kutzbach and Vilhuber, 2017).\textsuperscript{13} Both types of areas are composed of counties, so it is straightforward to map our county-level data into metropolitan areas or commuting zones. A slight complication is that definitions of metropolitan areas and commuting zones change over time; we use Core Based Statistical Areas (CBSAs) as defined by OMB in December 2003 and commuting zones as defined by USDA and based on the 2000 census. Although we focus on metropolitan areas because of their greater size and thicker labor markets, we show that our main results are robust to using commuting zones, which unlike metropolitan areas cover the entire United States.\textsuperscript{14}

3.2 Empirical Strategy

Our empirical strategy relies on cross-sectional variation in sudden employment changes that occur during nationwide recessions. We use this variation to estimate how the post-recession evolution of local labor market outcomes varies with the severity of each recession.

Our preferred approach is to estimate the following regression:

\begin{equation}
  y_{i,t} - y_{i,t-2} = s_i \delta_t + x_i \beta_t + \varepsilon_{i,t},
\end{equation}

where $y_{i,t}$ is a measure of local economic activity in location $i$ and year $t$; $s_i$ is the severity of the recession, measured as the log employment change in location $i$ from the nationwide peak to trough (multiplied by $-1$); $x_i$ is a vector of time-invariant control variables; and $\varepsilon_{i,t}$ is an error term. The term $y_{i,t-2}$ is the outcome measure in location $i$ two years before the nationwide recession start,

\textsuperscript{12}We do not examine counties because these are often too small to constitute local labor markets, our area of focus.

\textsuperscript{13}Metropolitan statistical areas are defined by the Office of Management and Budget (OMB) as having “at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties” (Office of Management and Budget, 2003). Commuting zones are defined based on commuting patterns and do not have a minimum population threshold or urban requirement (Tolbert and Sizer, 1996).

\textsuperscript{14}Metropolitan areas, consistently defined, cover 80–90 percent of people and jobs throughout our sample, with this share growing over time.
so that the left-hand side of equation (1) is the within-location change in the outcome relative to a fixed, pre-recession period.

The key parameter of interest, $\delta_t$, describes the relationship between the change in employment during the recession and the change in local economic activity as of year $t$. Because the left-hand side of equation (1) is a within-location change, this approach controls for time-invariant cross-sectional differences. We normalize the $\delta_t$ coefficient so that $\delta_{t_0-2} = 0$ to facilitate comparisons across recessions. We choose $t_0 - 2$ as the normalization year because the exact timing of recessions is uncertain and there is variation in when aggregate economic indicators decline. The $\delta_t$ parameters vary freely across years, which is useful for identifying empirical patterns without imposing possibly incorrect constraints. This reduced-form approach can capture a wide variety of demand and supply adjustments after the recession.

We measure local recession severity using annual employment data from BEAR. We modify NBER recession peak and trough dates to account for our use of annual data. Specifically, we construct $s_i$ using the log employment change for each geography between 1973–1975, 1979–1982, 1989–1991, 2000–2002, and 2007–2009. Using fixed national timings for each recession, rather than location-specific peak-to-trough periods, introduces some measurement error but minimizes the risk of endogeneity. We use wage and salary employment (private and public) to measure recession severity, as coverage of the self-employed is incomplete and varies over time. Variation across areas in employment losses during recessions can arise from differences in industrial specialization (e.g., recessions could decrease demand for automobiles) or even finer differences in the products that are made in an area (e.g., recessions could particularly decrease demand for more expensive trucks and SUVs). Idiosyncratic shocks to a single large firm also could generate local employment losses (c.f., Gabaix, 2011; Salgado, Guvenen and Bloom, 2020).

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15 Because we show the entire range of estimates of $\delta_t$, it is straightforward to see how our estimates would change with a different normalization year.

16 QCEW is an alternative. While quarterly data would allow us to use the NBER recession quarters to measure recession severity, they would also require a seasonal adjustment. In practice, as we show below, results are robust to using either source to measure severity.

Estimates of $\delta_t$ can be interpreted as isolating the differential response of local economic outcomes with respect to recession severity if $s_i$ is exogenous to changes in residual determinants of local labor market outcomes, $\varepsilon_{i,t}$, conditional on the controls in the regression. In addition to controlling for time-invariant differences across local areas, we include several variables in $x_i$ to bolster the validity of this interpretation. First, we include Census division fixed effects to flexibly capture broad shifts in local labor demand and supply that are not driven by recessions, such as the rise of the Sunbelt (Glaeser and Tobio, 2008). Second, we include pre-recession population growth to adjust for secular shifts in local labor supply.\textsuperscript{18} The coefficient vector on these controls, $\beta_t$, varies freely across years for increased flexibility. In unreported results, we find that estimates are very similar when additionally controlling for pre-recession employment growth with time-varying coefficients. Estimates of $\delta_t$ for pre-recession years allow us to directly examine the presence of pre-trends, and estimates of $\delta_t$ for post-recession years shed light on whether areas that experience larger employment losses during recessions are differentially exposed to non-recession economic shocks (which would show up as subsequent spikes or jumps in $\delta_t$). We cluster standard errors at the metro level to allow for arbitrary autocorrelation in the error term $\varepsilon_{i,t}$.

3.3 The Severity of Recessions Across Time and Space

Before moving to estimates of equation (1), we describe the characteristics of the five recessions that are our focus. Figure 2 displays aggregate seasonally adjusted, nonfarm employment from the Current Employment Statistics from 1969 to 2019. Nationwide employment more than doubled over this period. This growth was interrupted by five recessions (combining the two in the early 1980s), as indicated by the vertical shaded bars in the graph. While there is little consensus on the macroeconomic causes of each recession, the drivers almost certainly differ (Temin, 1998).

\textsuperscript{18}Controlling for baseline levels or pre-trends of economic outcomes is common (e.g., Autor, Dorn and Hanson, 2013; Dix-Carneiro and Kovak, 2017; Hershbein and Kahn, 2018). Given the challenge of controlling directly for all relevant local labor supply shifters (e.g., due to a wide range of natural and cultural amenities), we opt to control for pre-recession population growth. We control for the log change in population for ages 0–14, 15–39, 40–64, and 65 and above. We construct these population variables using SEER data, which are available starting in 1969. The pre-recession population growth years are 1969–1973 (for the 1973–1975 recession), 1969–1979 (for the 1980–1982 recession), 1979–1989 (for the 1990–1991 recession), 1990–2000 (for the 2001 recession), and 1997–2007 (for the 2007–2009 recession).

Using annual data from BEAR, Table 1 shows the national changes in employment from peak to trough for each recession, both overall and for major industrial sectors. The recessions vary in overall magnitude, from a 3 percent employment decline during the Great Recession to a 1 percent increase from 1989 to 1991, with the others falling in between. Manufacturing and construction usually experience the largest employment decline, with the exception of construction during the 2001 recession, which was accompanied by a housing boom. The patterns of employment changes for other industries differ across recessions. The early 1990s downturn and the Great Recession were broad in scope, with most major industries experiencing an employment decline. The early 1980s recession was heavily concentrated in certain industries, including manufacturing and construction. Similarly, the recessions in 1973–1975 and 2001 saw flat or rising employment in several industries, including services. Our use of annual BEAR data masks some of the severe employment losses that are evident in monthly data.

These patterns suggest that areas with employment bases reliant on manufacturing or construction were more likely to suffer severe recessions, although the variation across recessions in other industries implies that the same areas are not necessarily hit each time. Figure 3 shows the log employment change across metropolitan areas during each recession. While many areas in the Midwest Rust Belt fare poorly in each recession, there is considerable heterogeneity for other areas. The Northeast, for example, is severely affected in the 1970s, 1990s, and 2001, but only modestly in the early 1980s and late 2000s. The Pacific Northwest fares relatively well in the 1970s and 1990s but is hit harder in the other three recessions. There is also ample variation across areas in severity within a given recession, with several areas actually gaining employment in each

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19 We use BEAR data rather than national Current Employment Statistics data to be consistent with our subsequent analysis, but the patterns are qualitatively similar.
Figure 4 displays the frequency with which each area experienced a severe recession over the sample horizon. We define a metropolitan area as having a severe recession if it experienced a log employment change worse than the median area for a given recession. The Detroit and Chicago metros, for example, experienced downturns worse than the median for all five recessions, while the Houston metro did so only in 2001. The distribution in severity frequency is roughly symmetric, with a similar number of metros experiencing zero or one severe recessions (112) as those experiencing four or five (105).

We show the serial correlation in recession severity in Table 2. Panel A shows the raw correlations across metros in log employment changes for each pair of recessions. As suggested by Figures 3 and 4, the serial correlation is positive, but moderate. Consistent with the different origins of the recessions as well as temporal changes in industrial mix, the pattern is not monotonic across time. We also show in Panel B the correlations within each of the nine Census divisions (i.e., after partialing out division fixed effects), and in Panel C the correlations after additionally controlling for pre-recession population growth. These controls tend to slightly reduce the magnitudes of the correlations, but positive serial correlation remains in a few cases. The regression estimates below suggest that serial correlation in recession severity has relatively little impact on our results. We also control for the severity of previous recessions as an additional robustness check and show that these controls do not appreciably change the results.

Table 3 describes the characteristics of metropolitan areas that experience a more versus less severe recession (defined as whether the log employment change is above or below the median). We measure these characteristics using the closest decennial census to the recession start year, except for the 2007–2009 recession, which is measured using the 2005–2009 ACS. Recessions tend to be more severe in places with higher population but slower pre-recession population growth, higher employment rates and earnings per capita, a higher manufacturing employment share, and a less educated workforce. The largest difference between areas that experience a more versus

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20Panels A and B of Appendix Figure A.1 present kernel densities of the demeaned and unadjusted log employment changes across metros for each recession.
less severe recession is the manufacturing employment share, though this difference has decreased considerably over time. Moreover, many of the differences are quite small. The variables in Table 3 include both sources of recession severity and factors that might influence the response of local areas to decreases in employment. We directly examine changes in some of these variables, while also examining changes in worker composition to better understand related mechanisms.\footnote{We examined whether post-recession changes in economic activity varied with pre-recession levels of these variables but found little evidence of such heterogeneity.}

4 The Post-Recession Evolution of Local Economic Activity

4.1 Employment

We begin with estimates of equation (1) for log employment in metropolitan areas. Each panel in Figure 5 shows separate estimates for each recession. We include four years before the start of the recession to capture any pre-trends, and we follow areas for 10 years after the recession trough. Specification 1, shown in red (circles), includes only Census division fixed effects in \( x_i \).

Our preferred specification 2 (solid blue line) also controls for pre-recession population growth for ages 0–14, 15–39, 40–64, and 65 and above. Specification 3 (green squares) adds the severity of the previous recession, which is possible for all but the 1973–1975 recession. Finally, specification 4 (orange triangles) further includes the severity of all previous recessions since 1973. In all cases we allow the coefficient vector \( \beta_t \) to vary freely across years.

Overall, there is some weak evidence of negative pre-trends from specification 1 for the 1980–1982, 1990–1991, and 2001 recessions, indicating that employment was gradually declining beforehand in areas that experienced a more severe recession. Controlling for pre-recession population growth eliminates these pre-trends.\footnote{For the 1990–1991 recession, there is evidence of a decrease in employment starting in 1988. A possible explanation for this pattern is that the Federal Reserve started to increase interest rates in early 1988 to fight inflation, and this increase in interest rates could have disproportionally affected areas harder hit by the subsequent recession.} Since population growth is calculated over the decade before the recession, it is likely we eliminate secular trends (such as growing migration to certain metros in the South and West).
The results in Figure 5 indicate that local employment losses during each recession have been extremely persistent. The recession severity variable $s_i$ is mechanically correlated with a large drop in log employment during the recession. There is no mechanical relationship for the post-recession coefficients, which show little to no recovery over the subsequent 10 years. Moreover, the confidence intervals imply that we can reject a return to initial peak employment in every post-recession year. The graphs also show that the persistent decline in employment is not affected by whether we control for the severity of previous recessions, and there is no evidence of subsequent discrete jumps, as might occur from a later shock. We obtain similar results when examining employment from County Business Patterns data (Appendix Figure A.2), where we also see a persistent decline in the number of establishments (Appendix Figure A.3).

Figure 6 illustrates how the relative changes identified by equation (1) translate into aggregate outcomes. Panel A shows the $\delta_t$ coefficients for the 1980–1982 recession from our preferred specification, and Panel B displays the implied evolution of mean log employment in metropolitan areas with a more versus less severe recession. Employment grows after 1982 in both areas, regardless of recession severity. However, the level of employment is persistently lower in areas where the recession was more severe; this is the relative change identified with cross-sectional variation.

Panel A of Table 4 summarizes the (preferred) specification 2 results 7–9 years after the recession trough. The equally-weighted average of elasticities across recessions is $-1.2$, which indicates that a 10 percent decrease in employment during the recession is followed by 12 percent lower employment 7–9 years later. Because recession severity varies both across recessions and across areas within a given recession (Appendix Figure A.1), we also report standardized coefficients. On average, a one-standard deviation employment decline leads to a 6 percent decrease in

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23Because we normalize the coefficient two years before the peak (i.e., $\delta_{t_{0-2}} = 0$), the coefficient at the trough need not be exactly $-1$, although the estimate is generally close to this number, reflecting flat pre-trends. The difference between coefficients from peak-to-trough mechanically equals $-1$ for the log employment regressions because the recession severity variable is constructed as the difference in log employment.

24We construct these conditional means using estimates of equation (1), holding all covariates besides recession severity at their mean value, and defining the gap between a more and less severe recession as a log employment change difference of $-0.12$ (equal to the difference in mean recession severity for areas with a log employment change below or above the median).

25We generate the results in this table by pooling the coefficients in equation (1) for post-trough years 7–9. Estimating a pooled coefficient summarizes the medium-term changes while also increasing precision.
employment 7–9 years after the recession trough.

The consequences of these decreases in employment depend on the degree of population response. We examine this next.

4.2 Population

In Figure 7 we present estimates of equation (1) where the dependent variable is the log of the total working-age population (15+). For brevity, we show only the results from specification 2, although the patterns are robust to specifications 3 and 4. We see no evidence of pre-trends and find sustained post-recession decreases in population in areas with greater job loss.\textsuperscript{26} Population continues to decline long after each recession ends, implying that harder-hit areas remain on a lower population-growth trajectory. The elasticities at recession trough are modest, between $-0.2$ and $-0.3$, but then double or even close to triple over the next decade.

Panel B of Table 4 presents summaries of these results. On average, a 10 percent decrease in employment during the recession is followed by a 5.6 percent decrease in population 7–9 years after the trough. After a one-standard deviation employment decrease, population falls by 2.9 percent on average. Consistent with the previously-documented decline in migration (Molloy, Smith and Wozniak, 2014; Dao, Furceri and Loungani, 2017), we find that post-recession declines in population have become smaller over time.

4.3 Employment-Population Ratio

Population declines by less than employment in areas that experience more severe recessions. This implies that employment-population ratios fall after each recession. To examine this pattern more directly, we use the log of the ratio of employment to working-age population as the dependent variable in equation (1).\textsuperscript{27}

\textsuperscript{26}The lack of pre-trends for the population results is not surprising, as we directly control for pre-recession population growth.

\textsuperscript{27}Our employment-population measure is the ratio of the count of jobs to the number of working-age people; because of multiple job-holding, it is not strictly comparable to official employment-population ratios, which represent the share of the population that is employed.
Figure 8 shows that employment-population ratios fall during recessions and remain below their pre-recession peaks, even a decade after recession’s end. As a consequence of the relatively flat employment trajectories and steady population declines, employment-population ratios generally show a slight recovery over time. Panel C of Table 4 reports summaries of these estimates 7–9 years post trough. The average elasticity is about $-0.7$. Given a mean employment-population ratio of about 60 percent, this elasticity implies that a 10 percent decrease in employment is followed by a 4.0 percentage point decline in the employment-population ratio. A one-standard deviation employment decline leads to a 3.1 percent (1.9 percentage point) decrease in the employment-population ratio on average.\textsuperscript{28}

The estimates in Table 4 facilitate a simple decomposition of the post-recession decline in employment, namely that the post-recession change in log employment equals the change in log population plus the change in the log employment-population ratio. On average, the decline in the log employment-population ratio accounts for about 54 percent of the decline in employment 7–9 years after recession trough, with the remaining 46 percent explained by the decline in population.\textsuperscript{29}

### 4.4 Per Capita Earnings

Local employment losses could be followed by broader changes than a persistent decline in the employment-population ratio. For example, as illustrated in Section 2, local labor markets could also face declines in wages, and reductions in employment could extend beyond the extensive margin to also affect hours worked. To understand the broader consequences of local employment losses, we examine changes in log per capita earnings. The results in Figure 9 show evidence of persistent reductions in per capita earnings following each recession. The average medium-term elasticity in Panel D of Table 4 is $-1.0$. A one-standard-deviation greater employment decline

\textsuperscript{28}These extensive-margin estimates do not preclude the possibility of intensive margin employment changes. Census and ACS microdata reveal declines in full-year and full-time, full-year employment rates, with somewhat imprecise but larger magnitudes for these outcomes than for overall employment rates.

\textsuperscript{29}The equally-weighted average coefficient in Table 4 is $-1.22$ for log employment and $-0.56$ for log population, so the post-recession decrease in population explains 46 percent ($=0.56/1.22$) of the decline in employment.
is followed by a 4.8 percent larger decrease in per capita earnings 7–9 years after the recession trough.\footnote{Our preferred earnings measure includes wages, salaries, and supplements (benefits), which are only available by place of work. We show in Appendix Figure A.4 that our findings are not sensitive to the place of residence versus place of work distinction.} \footnote{Recessions also could lower housing prices. Using average rent prices by metropolitan areas from the census and ACS, we estimate a long-run elasticity to employment changes across recessions of about $-0.6$. Assuming 30 percent of income is spent on housing, a one-standard deviation decrease in employment during a recession translates into roughly a 0.9 percent long-term decrease in expenditures due to lower housing costs. This could offset about 19 percent of the decrease in per capita earnings ($0.19 = 0.9/4.76$). However, this interpretation is complicated in that homeowners facing a similar housing price loss suffer a negative wealth effect (Campbell and Cocco, 2007; Mian, Rao and Sufi, 2013; Guren et al., 2021), which would lower households’ purchasing power.}

The definitions of the outcomes in Panels C–E of Table 4 facilitate a decomposition of the decline in earnings per capita. In particular, the change in log earnings per capita (panel D) equals the sum of the change in the log employment-population ratio (panel C) and the change in log earnings per worker (shown in Panel E). We find that about two-thirds of the post-recession decrease in earnings per capita is explained by the decline in the employment-population ratio, with the remaining one-third explained by the decrease in earnings per worker. Consequently, extensive margin employment adjustments are particularly important for the decrease in per capita earnings.

### 4.5 Robustness

Our results are robust to different measures of recession severity and different definitions of local labor markets. In particular, Appendix B.1 shows that our results are very similar when using private wage and salary employment from BEAR or QCEW data to measure recession severity. Appendix B.2 discusses results when measuring recession severity with the log employment change predicted by an area’s industry mix (Bartik, 1991). While there are several reasons to prefer the actual log employment change over the predicted log employment change, the results are generally similar. Finally, Appendix B.3 shows that our results are nearly identical when examining commuting zones instead of metropolitan areas.
5 Discussion

How should we rationalize the persistent declines in employment, population, employment-population ratios, earnings per capita, and earnings per worker? The conceptual framework in Section 2 suggests that these patterns are consistent with persistent downward shift in local labor demand and a labor supply curve that is less than perfectly elastic but more elastic than population. In this section we present additional evidence that supports this interpretation and provides additional context.

5.1 Supporting Evidence

A possible concern is that our estimates simply reflect the effects of secular changes in the economy, such as the decline in manufacturing. This issue is closely related to the hypothesis of Amior and Manning (2018), who argue that slow regional recoveries are partly due to serially correlated labor demand shocks, which could resemble secular changes in annual data. Several factors point against these interpretations in our setting.

Most importantly, there is little evidence that the persistent decline in local economic activity is driven by subsequent shocks that occur after recessions. If areas faced a severe recession and then a serially correlated shock a few years later, we would expect to see post-recession years with sharp decreases in employment. Except for the 1973–1975 recession, these sharp changes are not evident in Figure 5. Employment gradually declines after the 1990–1991 recession, but the vast majority of the employment decrease occurs during the recession. There is little evidence of further employment declines in the decade after the 1980–1982, 2001, and 2007–2009 recessions. Overall, these results suggest that serially correlated labor demand shocks play a minor role in our setting.

To explore this issue further, we estimate regressions that control for interactions between year indicators and the pre-recession share of employment in each of ten sectors: agriculture, construction, finance, government, manufacturing, mining, retail trade, services, utilities, and wholesale trade. These controls absorb changes in economic activity that are associated with industrial spe-
cialization. For example, areas that specialize in manufacturing might have experienced reductions in employment for the past 50 years, due to either secular change or repeated shocks. Industrial specialization is correlated with recession severity, so these controls could attenuate estimates of the post-recession decline in local economic activity. Nonetheless, the results in Figure 10 show that the estimated evolution of the employment-population ratio is very similar when including these controls. Our estimates of persistent post-recession declines do not simply reflect secular changes in manufacturing or other sectors.\footnote{We also have estimated regressions that control for interactions between year indicators and the \textit{pre-recession} log employment change predicted by pre-recession industrial structure (Bartik, 1991). Results are extremely similar when including this control, which further supports the conclusion that our estimates do not simply reflect secular decline.}

5.2 Contextualizing Evidence

5.2.1 Employment Declines across All Sectors

Are the employment losses shown in Figure 5 broad-based or concentrated in certain industries? To explore this question, Figure 11 shows estimates of equation (1), where the dependent variable is log employment in each sector. For simplicity and ease of presentation, we present estimates for specification 2 only and suppress confidence intervals. We find that, across recessions, the decline in employment is pervasive across sectors, as nearly every point estimate is below zero. Construction and manufacturing experience the largest short-term decreases, while government employment generally falls the least. The remaining industries tend to move similarly and lie in between, with no clear evidence in any case of an upward slope to suggest an eventual recovery.\footnote{We exclude agriculture and mining, which are small (especially in metropolitan areas) and highly spatially concentrated. We note the unusual positive pattern for utilities and transportation following the Great Recession. The confidence intervals for this series are wider than in previous recessions, and so we are hesitant to read much into these results, but it is possible that recent growth in freight transportation stemming from e-commerce has mitigated employment losses in this sector.} As noted in Figure 6, these relative employment losses need not reflect absolute employment losses.
5.2.2 Population Declines through Lower In-Migration

What explains the decline in population? We use the SOI data to examine this question for the two most recent recessions. Panels A and B of Figure 12 replicate the analysis of population for the 2001 and 2007–2009 recessions using the total number of exemptions in the tax data to proxy for population. The patterns are similar to those in Figure 7.

We decompose the net change in population into changes in in-migration, out-migration, and residual net births. This starts with the identity

\[
\text{pop}_{i,t} = \text{pop}_{i,t-1} + \text{inmig}_{i,t} - \text{outmig}_{i,t} + \text{netbirths}_{i,t},
\]

where \(\text{pop}_{i,t}\) is population in location \(i\) and year \(t\), \(\text{inmig}_{i,t}\) is the number of in-migrants between year \(t - 1\) and \(t\), \(\text{outmig}_{i,t}\) is the number of out-migrants, and \(\text{netbirths}_{i,t}\) is the number of births minus deaths. Iterating equation (2) forward and normalizing by a baseline population level, we have

\[
\frac{\text{pop}_{i,t}}{\text{pop}_{i,0}} - 1 = \sum_{j=1}^{t} \frac{\text{inmig}_{i,j}}{\text{pop}_{i,0}} - \sum_{j=1}^{t} \frac{\text{outmig}_{i,j}}{\text{pop}_{i,0}} + \sum_{j=1}^{t} \frac{\text{netbirths}_{i,j}}{\text{pop}_{i,0}}.
\]

Equation (3) provides the basis for an exact decomposition of population change into components for in-migration, out-migration, and net births.

As a starting point, Panels C and D of Figure 12 present results where the dependent variables are annual migration inflows and outflows, as well as residual net births, divided by the total number of exemptions in year \(t_0 - 2\).\(^{34}\) By recession trough, in-migration rates have fallen sharply, with a 10 percent decrease in employment during the recession being followed by a reduction in in-migration of about 1 percent of pre-recession population. Over the subsequent decade, in-migration rates recover only slightly, and by the end of the horizon they remain between 0.6 and 0.8

\(^{34}\)For these estimates, rather than the fixed difference of equation (1), we use an event study specification. Including measures of in-migration, out-migration, and net births as of year \(t_0 - 2\) in all models facilitates an exact decomposition using the regression coefficients.
percentage points below pre-recession values. Out-migration shows little response until after the recession has ended, although there is a slight upward pre-trend for the 2001 recession. Beginning in the year after the recession trough, however, out-migration rates steadily decline, with similar medium-term magnitudes as for in-migration.

To understand how these components contribute to the change in population, we construct cumulative sums of the coefficients in Panels C and D and divide these sums by the respective estimates in Panels A and B. When we also multiply the out-migration estimates by $-1$, the three transformed coefficients—in-migration, out-migration, and net births—sum to 1 and fully decompose the population changes found in the first two panels. These estimates are shown in Panels E and F. In both cases, we find that lower in-migration accounts for more than 100 percent of the medium-run decrease in population after recessions. In contrast to a story of individuals moving away from places where recessions are more severe, the decrease in out-migration dampens the population decline.\footnote{Monras (2020) also finds this pattern of relative population decline due to falling in-migration for the Great Recession, using variation in recession severity based on pre-recession per capita debt and the share of employment in non-tradable industries (see also Mian, Rao and Sufi, 2013). His calibrated general equilibrium model predicts that migration dissipates about 60 percent of the long-term impact on wages following the Great Recession.}

The lack of out-migration is a natural explanation for why the population response is incomplete.

5.2.3 Earnings Decline throughout the Distribution, via Lower Wages

We use census/ACS data to examine changes in the distribution of prime-age workers’ earnings. Specifically, we estimate a variant of equation (1) in which the dependent variables are pre-post recession changes.\footnote{We use the 1970 and 1980 censuses for the 1973–1975 recession, the 1980 and 1990 censuses for the 1980–1982 recession, the 1990 and 2000 censuses for the 1990–1991 recession, the 2000 census and 2005–2007 ACS for the 2001 recession, and the 2005–2007 and 2015–2017 ACS for the 2007–2009 recession. Because the variables used are based on the previous calendar year (census) or preceding 12 months (ACS), these changes straddle the periods when recessions occur.} We look at the mean and the 10th, 50th, and 90th percentiles of the log annual earnings distribution. The first row of Panel A of Table 5 shows that estimates for mean log earnings are similar to those from the BEAR data on log earnings per worker (Panel E of Table 4). The percentile estimates in the next three rows indicate that earnings fall throughout
the distribution, with larger changes at the 10th and 50th percentiles. These results are consistent with the finding that lower-earning demographic groups see larger employment declines during recessions (Hoynes, Miller and Schaller, 2012).

Does the reduction in earnings stem from a reduction in hours worked, a reduction in earnings per hour, or both? To answer this question, we use the census/ACS data to estimate regressions where the dependent variable is the change in average log annual, weekly, or hourly earnings. If the earnings losses are driven by a reduction in hours, hourly wages could be relatively unaffected several years later. On the other hand, if the recession slows wage growth or displaced workers are less likely to find good employer matches, hourly wage losses may explain more of the annual earnings declines. The results in Panel B of Table 5 indicate that the latter story better fits the data, and accord with Lachowska, Mas and Woodbury (2020), as the estimated declines in log hourly wages generally explain about three-quarters of the declines in log annual earnings. Decreases in work attachment at the intensive margin therefore explain relatively little of the persistent reduction of annual earnings among individuals who remain employed.37

5.2.4 The Role of Changes in the Composition of Residents

A remaining explanation for why recessions are followed by persistent declines in the employment-population ratio and per capita earnings is a change in worker composition due to differential migration responses. For example, if highly educated workers are more likely to leave an area in response to a decline in employment (Bound and Holzer, 2000; Wozniak, 2010; Notowidigdo, 2020), then average wages might fall because of a change in worker composition. Composition shifts are not a threat to our identification strategy, because our unit of analysis is an area rather than an individual, but they are an interesting mechanism to understand.

To quantify the role of composition shifts, we examine changes in residualized earnings. We regress log annual earnings of prime-age workers from the census and ACS on indicators for education (of which there are 11), age (30), sex (2), and race/ethnicity (4), plus interactions between

37These results do not conflict with our finding that the reduction in the employment-population ratio explains most of the decline in per capita earnings because our analysis of census/ACS data conditions on earnings being positive.
the education indicators and a quartic in age. We estimate these regressions separately for each year and use metro-area averages and percentiles of the residuals as dependent variables in our regressions. Panel C of Table 5 presents results for composition-adjusted wage and salary earnings. (Panel A, already discussed, shows non-adjusted results.) The composition-adjusted results tend to be somewhat smaller in magnitude, which indicates that composition shifts partly contribute to the persistent decline in earnings. However, the composition-adjusted estimates are still at least 75 percent as large as the unadjusted ones. This finding suggests that the persistent post-recession declines in average earnings are not primarily driven by changes in worker characteristics correlated with these variables.

The availability of annual population estimates by age from the SEER data allows us to use a complementary approach to explore the role of shifts in the age distribution of residents in each post-recession year. In particular, we predict the average change in the employment-population ratio due to changes in the age structure by combining estimates of the post-recession evolution of the share of the population age 15–39, 40–64, and over 65 (using SEER data) with the cross-sectional, pre-recession relationship between the age structure and the employment-population ratio.38 The results in Appendix Figure A.18 show that, while changes in the age structure do predict a decrease in the employment-population ratio, the predicted change is much smaller than the actual decrease in the employment-population ratio. Results are similar when repeating this exercise for log earnings per capita (not shown). In line with the results using individual-level data from the census and ACS, these findings suggest that shifts in the age of residents explain a limited share of the persistent local labor market declines.

### 5.2.5 Long-Run Results


38 We cannot use the same set of observed variables in this annual approach as we use with the long-difference for the census/ACS data because the annual SEER data lack population counts by education.
A.19 and A.20 show that employment and employment-population ratios had not recovered by 2019 for any recession. The partial recovery from the 1973–1975 recession reversed itself in the mid-1980s, after which employment-population ratios declined for the next 20 years. A similar pattern exists for the 1980–1982 recession: starting in the mid-1990s, the partial recovery reverses itself and employment-population ratios fall for several decades. The declines in employment-population ratios following the 1990–1991 and 2001 recessions were extremely stable over time. While it is possible that local areas with greater employment losses in each recession also were disproportionately exposed to other economic shocks over such an extended time horizon, we conclude that our results are not driven by the choice of a ten-year post-recession window.

6 A Comparison to Results from the Blanchard and Katz (1992) Model

Our finding that recessions are followed by persistent declines in the employment-population ratio and per capita earnings differs from the well-known results of Blanchard and Katz (1992)—hereafter BK—who find that the unemployment rate, the labor force participation rate, and wages return to trend within ten years after state-level employment declines. Our empirical strategy is fundamentally similar to BK, in that we both rely on cross-sectional variation in how local areas respond to employment changes. The key difference is that BK, and the many papers which follow their approach, estimate vector autoregressions (VARs) and then calculate impulse response functions, while we estimate regression models that impose no constraints on how coefficients vary across years. This section explores why our results differ. We show that finite sample bias, stemming from the relatively short time-series that researchers must rely on, leads to spurious recovery of impulse response functions in the BK VAR.

To facilitate discussion, we first introduce the BK VAR. The key variables are the annual change in log employment, $\Delta e_{i,t}$, the level of the log employment-labor force ratio, $el_{i,t}$, and the level of the log labor force-working age population ratio, $lp_{i,t}$. BK account for nationwide trends by differencing out the same variables for the aggregate U.S. economy. They estimate the following
recursive VAR using data from 1976–1990:

\[ \Delta e_{i,t} = \alpha_{i10} + \alpha_{i11}(L)\Delta e_{i,t-1} + \alpha_{i12}(L)e_{i,t-1} + \alpha_{i13}(L)l_{i,t-1} + \epsilon_{i,e,t}, \tag{4} \]

\[ e_{i,t} = \alpha_{i20} + \alpha_{i21}(L)\Delta e_{i,t} + \alpha_{i22}(L)e_{i,t-1} + \alpha_{i23}(L)l_{i,t-1} + \epsilon_{i,e,l,t}, \tag{5} \]

\[ l_{i,t} = \alpha_{i30} + \alpha_{i31}(L)\Delta e_{i,t} + \alpha_{i32}(L)e_{i,t-1} + \alpha_{i33}(L)l_{i,t-1} + \epsilon_{i,l,l,t}. \tag{6} \]

BK include two lags of each explanatory variable, along with state fixed effects \( \alpha_{i10}, \alpha_{i20}, \) and \( \alpha_{i30}. \) After estimating these equations (which can be done using three separate OLS regressions), BK construct the impulse response functions (IRFs) of each variable with respect to a 1 percent decrease in employment (i.e., a reduction in \( \epsilon_{i,e,t} \) of 0.01).\(^{39}\) Primary interest lies in these IRFs, which are constructed using only the coefficients in equations (4)–(6).

Figure 13 shows IRFs of log employment, the “unemployment rate” (one minus the log employment-labor force ratio), the log participation rate, and log population. We use BLS LAUS data from 1976–1990 to generate these results, which are extremely similar to Figure 7 of BK. Notably, the unemployment rate and participation rate completely recover within eight years.

Our preferred unit of geography is a metropolitan area or commuting zone. When using substate areas, reliable data on labor force participation are available for a limited time period at best.\(^{40}\) Consequently, the most comparable outcome is the employment-population ratio. The IRF of the log employment-population ratio can be constructed as the sum of the IRFs of the log employment-labor force ratio and the log labor force-population ratio. Panel B of Figure 13 shows this IRF from the BK model. As expected given the results in Panel A, the IRF shows complete recovery of the employment rate.

To facilitate the analysis below, we simplify the BK model in two ways. First, we estimate a two-equation VAR in first differences of log employment and levels of the log employment-

---

\(^{39}\)Because this is a recursive VAR, there is a natural unit of measurement for \( \epsilon_{i,e,t}. \) In contrast, a structural VAR does not feature this property (see, e.g., Stock and Watson, 2001).

\(^{40}\)The BLS provides county-level labor force estimates from 1990 onward. A separate series contains county-level labor force estimates from 1976–1989, but the BLS stresses that this series is not comparable to the 1990-forward series. Both data sets rely substantially on extrapolations from statistical models, as household surveys are not large enough to reliably measure unemployment and labor force for most counties.
population ratio, $e_{p,t}$. Second, we include only one lag of each variable. The resulting recursive VAR is:

$$\Delta e_{i,t} = \tilde{\alpha}_{i10} + \tilde{\alpha}_{i11} \Delta e_{i,t-1} + \tilde{\alpha}_{i12} e_{p,t-1} + \tilde{\epsilon}_{i,e,t},$$  \hspace{1cm} (7)$$

$$e_{p,t} = \tilde{\alpha}_{i20} + \tilde{\alpha}_{i21} \Delta e_{i,t} + \tilde{\alpha}_{i22} e_{p,t-1} + \tilde{\epsilon}_{i,lp,t}.$$  \hspace{1cm} (8)

These simplifying assumptions have little impact on the estimated IRF of the log employment-population ratio, as shown in Panel B of Figure 13.

Equations (7) and (8) permit simpler expressions of the IRF in terms of the underlying parameters. Consider a one-time change in log employment in period $t$ through $\tilde{\epsilon}_{i,e,t}$. The subsequent impacts on the log employment-population ratio are:

$$\frac{d e_{p,i,t}}{d \tilde{\epsilon}_{i,e,t}} = \tilde{\alpha}_{21},$$  \hspace{1cm} (9)$$

$$\frac{d e_{p,i,t+1}}{d \tilde{\epsilon}_{i,e,t}} = \tilde{\alpha}_{21}^2 \tilde{\alpha}_{21} + \tilde{\alpha}_{21}^2 \tilde{\alpha}_{11} + \tilde{\alpha}_{21} \tilde{\alpha}_{22},$$  \hspace{1cm} (10)$$

$$\frac{d e_{p,i,t+2}}{d \tilde{\epsilon}_{i,e,t}} = \tilde{\alpha}_{21}^3 \tilde{\alpha}_{12}^2 + 2 \tilde{\alpha}_{21}^2 \tilde{\alpha}_{11} \tilde{\alpha}_{12} + 2 \tilde{\alpha}_{21}^2 \tilde{\alpha}_{22} \tilde{\alpha}_{12} + \tilde{\alpha}_{21} \tilde{\alpha}_{11}^2 + \tilde{\alpha}_{21} \tilde{\alpha}_{22}^2 + \tilde{\alpha}_{21} \tilde{\alpha}_{11} \tilde{\alpha}_{22}.$$.  \hspace{1cm} (11)

Similar expressions exist for the IRF at later horizons, but these first few periods are adequate to highlight some important takeaways. First, bias in the OLS estimates of equations (7) and (8) can generate bias in the IRF, because the IRF is a function of the coefficients in these equations. Second, bias in the IRF can be a nonlinear function of bias in the coefficients, because the IRF is a nonlinear function of these coefficients. Third, bias in the IRF can increase in importance over time. For example, if the OLS estimates are attenuated, this bias generates an IRF that can converge towards zero even if the true IRF does not. This arises because the exponents in the IRF increase with time, magnifying attenuation bias.\footnote{More generally, if $a \in (0, 1)$ is an attenuation factor, then $(ax)^t$ converges to zero faster than $x^t$.}

The potential for finite sample attenuation bias in autoregressive models, including VARs, has long been recognized (e.g., Hurwicz, 1950; Shaman and Stine, 1988; Stine and Shaman, 1989;
Pope, 1990; Lucas, 1992; Kilian, 1998, 1999; Kilian and Lütkepohl, 2017). This bias arises because residuals are not independent of all regressors in an autoregression, since regressors are lagged dependent variables.

To explore this issue further, we conduct a Monte Carlo study of finite sample bias. We focus on a data generating process (DGP) where a decrease in employment leads to a persistent reduction in the employment-population ratio. We do not argue that this is the true DGP. Instead, this exercise illustrates how the BK VAR can fail to estimate a persistent decline in the employment-population ratio when one is actually present. For the Monte Carlo exercise we assume that log employment is a random walk:

\[ e_{i,t} = e_{i,t-1} + \varepsilon_{i,e,t}, \]  

(12)

and that log population depends on changes in log employment as follows:

\[ p_{i,t} = p_{i,t-1} + (1 - \phi) \Delta e_{i,t} + \varepsilon_{i,p,t}. \]  

(13)

This implies that the log employment-population ratio is:

\[ ep_{i,t} = ep_{i,t-1} + \phi \Delta e_{i,t} - \varepsilon_{i,p,t}. \]  

(14)

In terms of equations (7) and (8), this DGP sets \( \tilde{\alpha}_{10} = \tilde{\alpha}_{20} = 0 \) (state fixed effects do not matter), \( \tilde{\alpha}_{11} = \tilde{\alpha}_{12} = 0 \) (log employment is a random walk), \( \tilde{\alpha}_{21} = \phi \), and \( \tilde{\alpha}_{22} = 1 \). Changes in log employment have a permanent effect on the log employment-population ratio, with the true IRF equal to \( \phi \) at all horizons.

\(^{42}\)Kilian (1998, 1999) specifically addresses bias in impulse responses. The methods discussed in these papers allow for bias-corrected confidence intervals of impulse responses, but we focus on point estimates here for simplicity. In general, “there is no consensus in the literature that impulse responses should be estimated based on bias-adjusted slope parameters rather than the original [least squares] estimates” (Kilian and Lütkepohl, 2017, p. 37).

\(^{43}\)In his discussion of BK, Lucas (1992) raises a concern about small sample bias, but speculates that such bias does not drive their conclusions. Amior and Manning (2018) theorize that the limited number of lags in the BK model could explain why BK find faster recovery than Amior and Manning (2018). Bias caused by a limited number of time periods—which we explore here—is distinct from whether the VAR has the appropriate lag structure.
We calibrate the DGP using state-level LAUS data. We assume that all variables are distributed normally. The first period mean and variance of $e_{i,t}$ and $p_{i,t}$ equal those observed in the 1976 LAUS data, and the variances of $\varepsilon_{i,e,t}$ and $\varepsilon_{i,p,t}$ approximate the variance of log employment and population in subsequent years.\footnote{In particular we set $e_{i,0} \sim \mathcal{N}(13.94, 1.00^2)$, $p_{i,0} \sim \mathcal{N}(14.49, 1.02^2)$, $\varepsilon_{i,e,t} \sim \mathcal{N}(0, 0.015^2)$, and $\varepsilon_{i,p,t} \sim \mathcal{N}(0, 0.015^2)$.} We focus on the case where $\phi = 0.75$, with 50 cross-sectional observations and different time-series lengths, $T$.

Panel A of Figure 14 plots the true IRF along with average estimates across 499 Monte Carlo simulations. The true IRF reveals a persistent decrease in the employment-population ratio following a one-time decrease in employment. For $T = 15$, which is approximately the number of years available to BK when they wrote their paper, finite sample bias leads to rapid recovery of the employment-population ratio. Ten years after the shock, the IRF estimate is downward-biased (in absolute value) by 89 percent. This bias remains very large for $T = 25$ and $T = 50$. Because previous work on local labor markets uses annual data, the relevant value of $T$ ranges from 15 to 50. For $T = 100$ the bias remains sizable, at 25 percent ten years after the shock. Even for $T = 500$, finite sample bias incorrectly implies a gradual recovery.\footnote{Appendix Table A.3 reports the underlying bias in estimates of the parameters of equations (7) and (8) for various values of $T$. All parameters are biased. While this bias is modest in many cases, it is amplified in the IRF. The IRF bias is of primary interest, because the IRF is used to quantify the extent of recovery.} The bias stems from an insufficient number of time series observations, so instrumental variables, which rely on asymptotic consistency, do not solve this problem in general. Indeed, we find that a sufficiently strong instrumental variable (as has been used in previous work) generates nearly identical results in our DGP (in which an instrument is not needed to obtain consistent estimates).

Regressions that mirror our preferred specification in equation (1) do not suffer from finite sample bias due to small $T$ in this setting. To show this, we use the same DGP and estimate the following regression:

$$e_{p_{i,t}} - e_{p_{i,0}} = \Delta e_{i} \delta t + \beta t + \varepsilon_{i,t},$$  \hspace{1cm} (15)
effect. To be consistent with the VAR IRFs, we normalize the coefficient $\delta_0 = 0$. This is the direct analog of equation (1). Under this DGP, we have $\delta_t = -0.75$ for all years $t \geq 1$. Hence, the coefficient $\delta_t$ and the IRF coincide in population for all years after the measured log employment change. Panel B of Figure 14 shows that there is no systematic bias in estimates of $\delta_t$, regardless of $T$.\footnote{This Monte Carlo exercise does not rule out other potential sources of bias when estimating equation (1), but we prefer to explore those issues using actual data.}

In sum, finite sample bias can lead the BK VAR to find evidence of recovery when there is none. The regressions that we estimate are not subject to this finite sample bias in empirically relevant DGPs. We believe this is the main explanation for why we find widespread evidence of persistent declines in employment-population ratios (and per capita earnings), while papers estimating the BK VAR generally do not.\footnote{We find similar patterns if we estimate our regressions on state-level data, rather than metro-level data, so the choice of geographic unit does not explain the difference.}

To be clear, we do not claim that all VARs are incapable of identifying persistent changes. However, finite sample bias is evident in DGPs that are relevant for VARs estimated in previous work on local labor markets.

7 Conclusion

Studying recessions over the course of 50 years, this paper shows that local employment losses that emerge during recessions are followed by long-lasting relative declines in employment, population, employment-population ratios, and per capita earnings. These patterns are consistent with harder-hit areas facing a persistent decline in labor demand relative to other areas, with labor supply being insufficiently responsive to restore pre-recession employment-population ratios and wages. One explanation for why these results have not been shown before is that an influential approach in the literature—estimating vector autoregressions and calculating impulse response functions as in Blanchard and Katz (1992)—can incorrectly find convergence after a persistent decline in local employment because of finite sample bias. In contrast, the regressions that we estimate do not suffer from this bias.
Cross-sectional variation in recession severity allows us to estimate relative changes by comparing local labor markets that experience a more versus less severe recession. This variation, however, does not allow us to identify absolute changes in local economic activity following recessions (e.g., Nakamura and Steinsson, 2014). Nonetheless, the persistent relative changes we find raise the concern that the capabilities of workers in some areas remain underutilized. This “direct effect” could lower aggregate output. At the same time, there could be an offsetting “indirect effect” if recessions reallocate employment to more productive areas. We examine this possibility through simple back-of-the-envelope calculations, described in Appendix B.4, and find no evidence of such productivity-enhancing reallocation. Fully assessing the impacts of persistent local labor market declines on aggregate output requires additional assumptions about the counterfactual evolution of economic activity in the absence of recessions, which we leave for future work.

Irrespective of the aggregate consequences of local labor market declines following recessions, our findings have important implications for labor market dynamism, the economic opportunities of workers and their children, and optimal policy responses. Our results show that recessions are followed by a sizable reallocation of employment across space. Local areas that experience more severe recessions see a persistent decline in employment across all sectors. At the same time, we find reductions in both in-migration and out-migration after local employment losses, which suggests that individuals are limited in their ability or willingness to move across areas to equilibrate shifts in labor demand. Moreover, the persistent decrease in local economic activity limits the opportunities available to both adults and children in these places. In response to these changes, investments in job creation and skill development could play an important role in boosting local economic activity. Such policies also could forestall the associated reduction in economic mobility for children (Stuart, 2022). Currently, the vast majority of policy responses to recessions focus on short-term conditions. Our results imply that additional consideration should be paid to recessions’ long-term consequences.
References


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Manson, Steven, Jonathan Schroeder, David Van Riper, and Steven Ruggles. 2019. “IPUMS National Historical Geographic Information System: Version 14.0 [Database].”


dent.


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Table 1: Aggregate Employment Changes, by Recession

<table>
<thead>
<tr>
<th></th>
<th>Share of peak year emp.</th>
<th>Log emp. change</th>
<th>Emp. change</th>
<th>Share of peak year emp.</th>
<th>Log emp. change</th>
<th>Emp. change</th>
<th>Share of peak year emp.</th>
<th>Log emp. change</th>
<th>Emp. change</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td><strong>1973–1975 Recession</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1.000</td>
<td>0.004</td>
<td>421,100</td>
<td>1.000</td>
<td>0.010</td>
<td>1,123,200</td>
<td>1.000</td>
<td>0.011</td>
<td>1,531,000</td>
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<tr>
<td>Manufacturing</td>
<td>0.216</td>
<td>−0.090</td>
<td>−1,758,600</td>
<td>0.196</td>
<td>−0.110</td>
<td>−2,230,100</td>
<td>0.150</td>
<td>−0.049</td>
<td>−962,800</td>
</tr>
<tr>
<td>Services</td>
<td>0.203</td>
<td>0.053</td>
<td>1,041,400</td>
<td>0.220</td>
<td>0.103</td>
<td>2,606,900</td>
<td>0.276</td>
<td>0.060</td>
<td>2,264,500</td>
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<tr>
<td>Government</td>
<td>0.177</td>
<td>0.046</td>
<td>792,000</td>
<td>0.168</td>
<td>0.008</td>
<td>149,000</td>
<td>0.156</td>
<td>0.023</td>
<td>493,000</td>
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<tr>
<td>Retail Trade</td>
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<td>0.010</td>
<td>153,300</td>
<td>0.161</td>
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<td>359,600</td>
<td>0.168</td>
<td>0.005</td>
<td>110,800</td>
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<td>Finance, Insurance, Real Estate</td>
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<td>0.027</td>
<td>192,700</td>
<td>0.079</td>
<td>0.037</td>
<td>322,200</td>
<td>0.080</td>
<td>−0.014</td>
<td>−146,000</td>
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<td>Transportation and Public Utilities</td>
<td>0.054</td>
<td>−0.018</td>
<td>−91,400</td>
<td>0.052</td>
<td>0.003</td>
<td>17,400</td>
<td>0.048</td>
<td>0.034</td>
<td>220,600</td>
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<tr>
<td>Construction</td>
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<td>−0.084</td>
<td>−410,000</td>
<td>0.054</td>
<td>−0.096</td>
<td>−536,900</td>
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<td>−0.065</td>
<td>−451,500</td>
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<tr>
<td>Wholesale Trade</td>
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<td>0.073</td>
<td>341,800</td>
<td>0.052</td>
<td>0.008</td>
<td>44,900</td>
<td>0.050</td>
<td>−0.012</td>
<td>−76,200</td>
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<tr>
<td>Mining</td>
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<td>0.140</td>
<td>114,100</td>
<td>0.011</td>
<td>0.264</td>
<td>350,800</td>
<td>0.008</td>
<td>−0.025</td>
<td>−26,000</td>
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<td>Agriculture, Forestry, Fisheries</td>
<td>0.006</td>
<td>0.073</td>
<td>45,800</td>
<td>0.008</td>
<td>0.043</td>
<td>39,400</td>
<td>0.010</td>
<td>0.077</td>
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<tr>
<td><strong>2001 Recession</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1.000</td>
<td>−0.000</td>
<td>−62,700</td>
<td>1.000</td>
<td>−0.034</td>
<td>−5,866,000</td>
<td>1.000</td>
<td>−0.034</td>
<td>−5,866,000</td>
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<tr>
<td>Manufacturing</td>
<td>0.109</td>
<td>−0.120</td>
<td>−2,004,900</td>
<td>0.082</td>
<td>−0.147</td>
<td>−1,982,600</td>
<td>0.082</td>
<td>−0.147</td>
<td>−1,982,600</td>
</tr>
<tr>
<td>Services</td>
<td>0.409</td>
<td>0.022</td>
<td>1,504,500</td>
<td>0.432</td>
<td>−0.012</td>
<td>−886,900</td>
<td>0.432</td>
<td>−0.012</td>
<td>−886,900</td>
</tr>
<tr>
<td>Government</td>
<td>0.141</td>
<td>0.027</td>
<td>638,000</td>
<td>0.137</td>
<td>0.018</td>
<td>452,000</td>
<td>0.137</td>
<td>0.018</td>
<td>452,000</td>
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<tr>
<td>Retail Trade</td>
<td>0.114</td>
<td>−0.015</td>
<td>−268,300</td>
<td>0.107</td>
<td>−0.064</td>
<td>−1,171,600</td>
<td>0.107</td>
<td>−0.064</td>
<td>−1,171,600</td>
</tr>
<tr>
<td>Finance, Insurance, Real Estate</td>
<td>0.082</td>
<td>0.019</td>
<td>260,100</td>
<td>0.094</td>
<td>0.025</td>
<td>426,900</td>
<td>0.094</td>
<td>0.025</td>
<td>426,900</td>
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<tr>
<td>Construction</td>
<td>0.059</td>
<td>0.013</td>
<td>128,500</td>
<td>0.064</td>
<td>−0.190</td>
<td>−1,975,100</td>
<td>0.064</td>
<td>−0.190</td>
<td>−1,975,100</td>
</tr>
<tr>
<td>Transportation and Public Utilities</td>
<td>0.038</td>
<td>−0.022</td>
<td>−133,000</td>
<td>0.037</td>
<td>−0.061</td>
<td>−385,500</td>
<td>0.037</td>
<td>−0.061</td>
<td>−385,500</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>0.039</td>
<td>−0.027</td>
<td>−169,900</td>
<td>0.037</td>
<td>−0.070</td>
<td>−443,300</td>
<td>0.037</td>
<td>−0.070</td>
<td>−443,300</td>
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<tr>
<td>Mining</td>
<td>0.005</td>
<td>−0.012</td>
<td>−9,000</td>
<td>0.006</td>
<td>0.107</td>
<td>114,300</td>
<td>0.006</td>
<td>0.107</td>
<td>114,300</td>
</tr>
<tr>
<td>Agriculture, Forestry, Fisheries</td>
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<td>−0.010</td>
<td>−8,700</td>
<td>0.005</td>
<td>−0.017</td>
<td>−14,200</td>
<td>0.005</td>
<td>−0.017</td>
<td>−14,200</td>
</tr>
</tbody>
</table>


Source: Authors’ calculations using Bureau of Economic Analysis Regional Economic Accounts (BEAR) data.
Table 2: Correlation of Metropolitan Area Recession Severity

<table>
<thead>
<tr>
<th>Change in Log Employment During Recession Years</th>
<th>Panel A: Unadjusted</th>
<th>Panel B: Adjusted for Census division</th>
<th>Panel C: Adjusted for Census division and pre-recession population growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973–75</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980–82</td>
<td>0.386</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>1989–91</td>
<td>0.459</td>
<td>0.154</td>
<td>1.000</td>
</tr>
<tr>
<td>2000–02</td>
<td>0.446</td>
<td>0.412</td>
<td>0.281</td>
</tr>
<tr>
<td>2007–09</td>
<td>0.354</td>
<td>0.210</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Panel B: Adjusted for Census division

| 1973–75                                       | 1.000               |                                     |                                     |                                     |                                     |
| 1980–82                                       | 0.327               | 1.000                                |                                     |                                     |                                     |
| 1989–91                                       | 0.275               | 0.170                                | 1.000                                |                                     |                                     |
| 2000–02                                       | 0.291               | 0.304                                | 0.234                                | 1.000                                |                                     |
| 2007–09                                       | 0.363               | 0.071                                | −0.044                               | 0.091                                | 1.000                                |

Panel C: Adjusted for Census division and pre-recession population growth

| 1973–75                                       | 1.000               |                                     |                                     |                                     |                                     |
| 1980–82                                       | 0.258               | 1.000                                |                                     |                                     |                                     |
| 1990–91                                       | 0.161               | 0.018                                | 1.000                                |                                     |                                     |
| 2000–02                                       | 0.144               | 0.084                                | 0.098                                | 1.000                                |                                     |
| 2007–09                                       | 0.400               | 0.279                                | 0.050                                | 0.212                                | 1.000                                |

Notes: Table reports correlations of log wage and salary employment changes across recessions for 358 metropolitan areas. Panel B reports correlations after partialling out Census division fixed effects, and Panel C partials out Census division fixed effects and pre-recession population growth. Source: Authors’ calculations using BEAR data.
Table 3: Characteristics of Metropolitan Areas with More versus Less Severe Recessions

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Less Severe</td>
<td>More Severe</td>
<td>Less Severe</td>
<td>More Severe</td>
<td>Less Severe</td>
</tr>
<tr>
<td>Population (1000s)</td>
<td>333.1</td>
<td>595.4</td>
<td>552.9</td>
<td>430.6</td>
<td>329.8</td>
</tr>
<tr>
<td>Log population growth</td>
<td>0.090</td>
<td>0.066</td>
<td>0.247</td>
<td>0.108</td>
<td>0.137</td>
</tr>
<tr>
<td>Employment-population ratio</td>
<td>0.518</td>
<td>0.537</td>
<td>0.534</td>
<td>0.547</td>
<td>0.546</td>
</tr>
<tr>
<td>Manufacturing share</td>
<td>0.141</td>
<td>0.254</td>
<td>0.140</td>
<td>0.236</td>
<td>0.131</td>
</tr>
<tr>
<td>Real earnings per capita (1000s)</td>
<td>19.7</td>
<td>21.0</td>
<td>21.5</td>
<td>23.2</td>
<td>23.5</td>
</tr>
<tr>
<td>HS degree+ share</td>
<td>0.562</td>
<td>0.504</td>
<td>0.677</td>
<td>0.656</td>
<td>0.764</td>
</tr>
<tr>
<td>BA+ share</td>
<td>0.120</td>
<td>0.096</td>
<td>0.172</td>
<td>0.142</td>
<td>0.195</td>
</tr>
<tr>
<td>Nonwhite share</td>
<td>0.145</td>
<td>0.133</td>
<td>0.209</td>
<td>0.122</td>
<td>0.189</td>
</tr>
<tr>
<td>Foreign-born share</td>
<td>0.029</td>
<td>0.027</td>
<td>0.048</td>
<td>0.028</td>
<td>0.045</td>
</tr>
</tbody>
</table>

Notes: Population, employment-population ratio, manufacturing share of employment, and real per capita earnings are measured two years before the recession start year. The last four rows are measured as of the closest decennial census to the recession start year, except for the 2007–2009 recession, which is measured from the 2005–2009 ACS. Population growth is from 1969 to 1973 for the 1973-1975 recession and over the previous ten years for the other recessions. We define an area as experiencing a more severe recession if its log employment change for a given recession is less than the median across the 358 CBSAs for that recession.

Source: Authors’ calculations of data from BEAR, decennial censuses and American Community Surveys (via IPUMS and NHGIS), and Surveillance, Epidemiology, and End Results (SEER).
Table 4: Summary of Changes in Metropolitan Area Economic Activity, 7–9 Years After Recession Trough

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Coefficient on log emp. decrease</td>
<td>−1.227</td>
<td>−0.935</td>
<td>−1.640</td>
<td>−1.529</td>
<td>−0.780</td>
</tr>
<tr>
<td></td>
<td>(0.185)</td>
<td>(0.137)</td>
<td>(0.151)</td>
<td>(0.130)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Implied change after 1 SD log emp. decrease</td>
<td>−0.069</td>
<td>−0.074</td>
<td>−0.074</td>
<td>−0.053</td>
<td>−0.030</td>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient on log emp. decrease</td>
<td>−0.642</td>
<td>−0.595</td>
<td>−0.634</td>
<td>−0.537</td>
<td>−0.378</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.078)</td>
<td>(0.127)</td>
<td>(0.100)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Implied change after 1 SD log emp. decrease</td>
<td>−0.036</td>
<td>−0.047</td>
<td>−0.029</td>
<td>−0.018</td>
<td>−0.015</td>
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<table>
<thead>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient on log emp. decrease</td>
<td>−0.585</td>
<td>−0.340</td>
<td>−1.006</td>
<td>−0.992</td>
<td>−0.402</td>
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<tr>
<td></td>
<td>(0.099)</td>
<td>(0.110)</td>
<td>(0.120)</td>
<td>(0.131)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>Implied change after 1 SD log emp. decrease</td>
<td>−0.033</td>
<td>−0.027</td>
<td>−0.046</td>
<td>−0.034</td>
<td>−0.016</td>
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</thead>
<tbody>
<tr>
<td>Coefficient on log emp. decrease</td>
<td>−0.760</td>
<td>−0.776</td>
<td>−1.060</td>
<td>−1.626</td>
<td>−0.764</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.167)</td>
<td>(0.148)</td>
<td>(0.225)</td>
<td>(0.177)</td>
</tr>
<tr>
<td>Implied change after 1 SD log emp. decrease</td>
<td>−0.042</td>
<td>−0.061</td>
<td>−0.048</td>
<td>−0.056</td>
<td>−0.030</td>
</tr>
</tbody>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Coefficient on log emp. decrease</td>
<td>−0.176</td>
<td>−0.437</td>
<td>−0.054</td>
<td>−0.634</td>
<td>−0.363</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.073)</td>
<td>(0.105)</td>
<td>(0.137)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Implied change after 1 SD log emp. decrease</td>
<td>−0.010</td>
<td>−0.035</td>
<td>−0.002</td>
<td>−0.022</td>
<td>−0.014</td>
</tr>
</tbody>
</table>

| SD of log employment change                           | 0.056   | 0.079   | 0.045   | 0.034| 0.039   |

Notes: Table reports estimates of equation (1), separately for each recession. The dependent variable is indicated in the panel title and constructed as the change relative to two years before the nationwide recession peak. The key independent variable is the change in log wage and salary employment during the recession from BEAR data. We pool estimates for years 7–9 after recession trough. All regressions control for division-year fixed effects and interactions between pre-recession population growth and year indicators. There are 358 metropolitan areas in the sample. Standard errors are clustered by metropolitan area.

Source: Authors’ calculations using BEAR and SEER data.
<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Log Annual Earnings, Without Composition Adjustment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average log earnings</td>
<td>−0.345</td>
<td>−0.405</td>
<td>−0.219</td>
<td>−0.628</td>
<td>−0.467</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.093)</td>
<td>(0.121)</td>
<td>(0.099)</td>
<td>(0.125)</td>
</tr>
<tr>
<td>10th percentile, log earnings</td>
<td>−0.725</td>
<td>−0.521</td>
<td>−0.650</td>
<td>−1.201</td>
<td>−0.398</td>
</tr>
<tr>
<td></td>
<td>(0.220)</td>
<td>(0.167)</td>
<td>(0.264)</td>
<td>(0.232)</td>
<td>(0.268)</td>
</tr>
<tr>
<td>50th percentile, log earnings</td>
<td>−0.274</td>
<td>−0.389</td>
<td>−0.093</td>
<td>−0.438</td>
<td>−0.580</td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.097)</td>
<td>(0.110)</td>
<td>(0.096)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>90th percentile, log earnings</td>
<td>−0.067</td>
<td>−0.255</td>
<td>−0.070</td>
<td>−0.404</td>
<td>−0.409</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.069)</td>
<td>(0.086)</td>
<td>(0.092)</td>
<td>(0.144)</td>
</tr>
<tr>
<td><strong>Panel B: Weekly and Hourly Earnings</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average log weekly earnings</td>
<td>−0.295</td>
<td>−0.395</td>
<td>−0.132</td>
<td>−0.488</td>
<td>−0.428</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.077)</td>
<td>(0.090)</td>
<td>(0.083)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Average log hourly earnings</td>
<td>−0.251</td>
<td>−0.355</td>
<td>−0.159</td>
<td>−0.404</td>
<td>−0.375</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.069)</td>
<td>(0.078)</td>
<td>(0.079)</td>
<td>(0.096)</td>
</tr>
<tr>
<td><strong>Panel C: Log Annual Earnings, With Composition Adjustment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average log earnings</td>
<td>−0.335</td>
<td>−0.307</td>
<td>−0.223</td>
<td>−0.739</td>
<td>−0.387</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.083)</td>
<td>(0.103)</td>
<td>(0.082)</td>
<td>(0.119)</td>
</tr>
<tr>
<td>10th percentile, log earnings</td>
<td>−0.746</td>
<td>−0.263</td>
<td>−0.628</td>
<td>−1.391</td>
<td>−0.313</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.162)</td>
<td>(0.210)</td>
<td>(0.225)</td>
<td>(0.272)</td>
</tr>
<tr>
<td>50th percentile, log earnings</td>
<td>−0.295</td>
<td>−0.301</td>
<td>−0.159</td>
<td>−0.580</td>
<td>−0.394</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.077)</td>
<td>(0.095)</td>
<td>(0.070)</td>
<td>(0.101)</td>
</tr>
<tr>
<td>90th percentile, log earnings</td>
<td>−0.192</td>
<td>−0.257</td>
<td>−0.107</td>
<td>−0.592</td>
<td>−0.357</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.068)</td>
<td>(0.063)</td>
<td>(0.082)</td>
<td>(0.149)</td>
</tr>
</tbody>
</table>

Notes: Table reports estimates of separate regressions for each recession. The dependent variable is indicated in the row titles and constructed as the change between pre-recession and post-recession years (1970 to 1980, 1980 to 1990, 1990 to 2000, 2000 to 2005–2007, and 2005–2007 to 2015–2017). The key independent variable is the change in log wage and salary employment during the recession from BEAR data. The underlying sample is limited to individuals age 25–54 and then collapsed to 358 metropolitan areas. All regressions control for division-year fixed effects and pre-recession population growth. The dependent variables in Panel C are constructed using residuals from regressing log earnings on indicators for education, indicators for age, an indicator for sex, and indicators for race/ethnicity (white/black/Hispanic/other), plus interactions between the education indicators and a quartic in age. Standard errors are robust to heteroskedasticity.

Source: Authors’ calculations using BEAR, decennial census, and ACS data.
Figure 1: The Response of Local Labor Markets to Labor Demand Shifts During Recessions

(a) Initial Equilibrium

(b) Temporary Demand Shift

(c)Persistent Demand Shift, Elastic Supply

(d) Persistent Demand Shift, Inelastic Supply

Notes: Figure shows three possible cases of how local labor markets might evolve after labor demand shifts. Panel A is the initial equilibrium, which depends on the labor demand curve (LD), labor supply curve (LS), and population supply curve (Pop). In Panel B, the demand shift is temporary, so employment, population, and wages revert to pre-recession levels. In Panel C, the demand shift is persistent, but labor supply and population are highly elastic, so employment and population fall, but wages and employment-population ratios recover to near their original level. In Panel D, the demand shift is persistent and labor supply and population are relatively inelastic. In this case, employment, population, wages, and employment rates all decline substantially.
Figure 2: Aggregate Employment and Recessions, 1969–2019

Notes: Figure shows seasonally adjusted national nonfarm employment. The shading indicates NBER national recession dates.
Notes: Each map shows the change in log employment from national peak to trough for 358 CBSAs (OMB vintage 2003 definitions) as described in the text. Areas in darker colors experienced larger employment losses.
Source: Authors’ calculations from BEAR.
Figure 4: Frequency of Severe Recessions, by Metropolitan Area, from 1973–2009

Notes: We define an area as experiencing a severe recession if its log employment change for a given recession is less than the median across the 358 CBSAs for that recession.
Source: Authors’ calculations from BEAR.
Figure 5: The Evolution of Metropolitan Area Log Employment and Changes in Log Employment During Recessions

(a) 1973–1975 Recession
(b) 1980–1982 Recession
(c) 1990–1991 Recession
(d) 2001 Recession
(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log wage and salary employment from BEAR data, and the key independent variable is the change in log wage and salary employment during the recession from BEAR data. Specifications are indicated by the legend. There are 358 metropolitan areas in the sample. Standard errors are clustered by metropolitan area. Source: Authors’ calculations using BEAR and SEER data.
Figure 6: Comparison of Relative Changes from Regressions and Absolute Changes: Log Employment and the 1980–1982 Recession

Notes: Panel A shows coefficient estimates from our main specification, as in Panel B of Figure 5. In Panel B, we use estimates of equation (1) to construct mean log employment for metropolitan areas with a more versus less severe recession (based on whether the log employment change is greater than or less than the median log employment change during the recession), holding all other covariates in the regression at their mean value. We do this for the 1980–1982 recession for purposes of illustration. Source: Authors’ calculations from BEAR data.
Figure 7: The Evolution of Metropolitan Area Log Population Age 15+ and Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log population age 15 and above. See notes to Figure 5.
Source: Authors’ calculations using BEAR and SEER data.
Figure 8: The Evolution of the Metropolitan Area Log Employment-Population Ratio and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log ratio of wage and salary employment to population age 15 and above. See notes to Figure 5.

Source: Authors’ calculations using BEAR and SEER data.
Figure 9: The Evolution of Metropolitan Area Log Real Per Capita Earnings and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log real earnings per capita (age 15+). See notes to Figure 5.

Source: Authors’ calculations using BEAR and SEER data.
Figure 10: The Evolution of Metropolitan Area Log Employment and Changes in Log Employment During Recessions, Robustness to Controlling for Pre-Recession Industrial Specialization

(a) 1973–1975 Recession
(b) 1980–1982 Recession
(c) 1990–1991 Recession
(d) 2001 Recession
(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log ratio of wage and salary employment to population age 15 and above. Model 1 is our preferred specification. Model 2 further controls for the pre-recession share of employment in agriculture, construction, finance, manufacturing, mining, retail trade, services, utilities, and wholesale trade (government is the omitted sector). Pre-recession employment is measured in 1973, 1979, 1989, 2000, and 2007. See notes to Figure 5.
Source: Authors’ calculations using BEAR and SEER data.
Figure 11: The Evolution of Metropolitan Area Log Employment by Sector and Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log employment from the indicated sector. We use BEAR data for the 1973–75, 1980–82, 1990–91, and 2007–09 recessions. We use QCEW data for the 2001 recession (due to SIC-NAICS industry seaming issues), except for government, which comes from BEAR. See notes to Figure 5. Source: Authors’ calculations using BEAR, SEER, and QCEW data.
Figure 12: The Evolution of Metropolitan Area In-Migration and Out-Migration and Changes in Log Employment During Recessions

(a) 2001, DV: Log Population

(b) 2007–2009, DV: Log Population

(c) 2001, DV: Population Component

(d) 2007–09, DV: Population Component

(e) 2001, Share of Total Change due to Components

(f) 2007–09, Share of Total Change due to Components

Notes: Figure reports estimates of an event study variant of equation (1), with lagged dependent variables on the right-hand-side instead of a fixed difference, separately for each recession. In Panels A and B, the dependent variable is the number of exemptions relative to the normalization year (1998 or 2005). In Panels C and D, the dependent variables are in-migration, out-migration, and residual net births, all relative to the number of exemptions in the normalization year. In Panels E and F, we divide cumulative sums of the coefficients from Panels C and D by the coefficients in Panels A and B; we multiply the out-migration coefficient by $-1$ so that the shares in Panels E and F add up to one. All regressions control for interactions between in-migration, out-migration, and residual net birth rates in the normalization year and year indicators, in addition to the baseline controls described in the notes to Figure 5. Source: Authors’ calculations using CBP, BEAR, and SOI data.
Figure 13: Impulse Response Functions to Negative Log Employment Shock from Vector Autoregressions

(a) Results from Blanchard and Katz (1992) Model

(b) Employment-Population Ratio

Notes: Figure shows impulse response functions of indicated variables with respect to a negative log employment shock. We construct impulse response functions for the BK VAR using estimates of equations (4)–(6). For the simplified VAR in Panel B, we use equations (7)–(8). Sample contains 48 continental states plus Washington, D.C. from 1976–1990. Source: Authors’ calculations using BLS LAUS data.
Figure 14: Comparison of Finite Sample Bias from Vector Autoregression Impulse Response Functions and Regressions

(a) Vector Autoregression Impulse Response Functions

(b) Regression Coefficients

Notes: Panel A displays impulse response functions of the log employment-population ratio with respect to a negative log employment shock based on estimates of equations (7)–(8). Panel B displays estimates of $\delta_t$ from the regression in equation (15). For both panels, we simulate data following equations (12)–(14). We set $\epsilon_{i,0} \sim \mathcal{N}(13.94, 1.00^2)$, $p_{i,0} \sim \mathcal{N}(14.49, 1.02^2)$, $\varepsilon_{i,e,t} \sim \mathcal{N}(0, 0.015^2)$, $\varepsilon_{i,p,t} \sim \mathcal{N}(0, 0.015^2)$, $\phi = -0.75$, and $N = 50$. Results are based on 499 Monte Carlo simulations.
Online Appendices

A  Data Appendix

A.1  Creating Consistent Geography Definitions over Time

We examine the impacts of recessions for different definitions of local areas: metropolitan areas and commuting zones. Each of these geography definitions changes over time. Moreover, each geography is composed of counties, and these, too, change over time. Metropolitan areas are periodically redefined by the Office of Management and Budget (OMB), and commuting zones are redefined decadally by the Department of Agriculture based on commuting questions in the census (in 1990 and 2000) or American Community Survey (2010). For ease of interpretation, we work with temporally-fixed definitions of metropolitan areas and commuting zones throughout our analyses. Specifically, we use Core-Based Statistical Areas (CBSAs) based on OMB definitions from June 2003 (drawn based on the 2000 census), and commuting zones based on the 2000 census. Since both these geographies are composed of counties, it is straightforward to aggregate county-level data using crosswalks released by the Office of Management and Budget (via the Census Bureau) or the Department of Agriculture.

To ensure we work with consistently defined counties, we use the Census Bureau’s county change database to recode county and county equivalents in the source data (BEAR, CBP, QCEW, SEER) to consistent definitions. We also restrict our analytic samples to the continental United States, excluding Alaska and Hawaii. Finally, we combine the independent cities in Virginia with their surrounding counties.

For analysis using microdata from the decennial census and ACS, counties are generally not observable. Rather, the ACS, 1990 census, and 2000 census contain indicators for the Public Use Microdata Area (PUMA), time-varying areas of at least 100,000 individuals. The 1970 and 1980 censuses instead contain county-group identifiers, which are conceptually similar but based on municipal and county units rather than Census tracts. We use population-weighted crosswalks available from the Missouri Census Data Center’s Geocorr application to map PUMAs to counties, and we use county group-county crosswalks available from IPUMS to map county groups to CBSAs. As described in the main text, for many of the analyses we first process the microdata and then collapse the relevant measures to our analytic geographies using the crosswalks.

A.2  Imputing Employment in Quarterly Census of Employment and Wages

For some robustness checks, we use the Bureau of Labor Statistics’ Quarterly Census of Employment and Wages (QCEW) as an alternative measure to the BEAR data for local area employment.

48Counties are the most stable, but occasionally change due to state legislative action or boundary disputes.
50See https://www.census.gov/programs-surveys/geography/technical-documentation/county-changes.html. For counties that change only names or codes, we use the modern versions, and we combine counties that either merge or split.
QCEW data are based on unemployment insurance records from each state, are one of the inputs used by BEA to construct its employment data, and constitute the data source used to benchmark the Current Employment Statistics for monthly jobs reports. Data are available starting in 1975 from the BLS website and provide employment and establishment counts, as well as aggregate and average weekly wages, for each county and industry, at annual, quarterly, and (for employment counts) monthly frequencies.\footnote{Aggregate employment for each geography is available from 1975; industry-level measures are available under NAICS coding from 1990 forward and SIC coding from 1975 through 2000.} However, data suppressions are common, especially earlier in the period. At the county level, data for small or highly concentrated industries (e.g., agriculture and mining) are often suppressed, although very small counties may even have total or total private employment suppressed. When these suppressions occur, all data for the county-industry-quarter are suppressed, unlike in County Business Patterns, described below. (For national series, used for constructing the “shifts” in the creation of predicted log employment changes as in Bartik (1991), suppression is not an issue.)

For total and total private (excluding government) employment, we impute missing employment counts at the county level through the following ordered process: 1) If total employment and government employment are reported but private employment is suppressed, we impute private employment as the difference between total and government;\footnote{We follow this rule for 1978 forward, when local and state government reporting was near universal; prior to this year, many jobs in local and state governments were not in the reporting universe, and available counts, when not suppressed, vastly underestimated government employment. See P.L. 94-566.} 2) If either total or private employment is missing in a given quarter, but not for all quarters in the year, we impute the one that is missing based on the average ratio (private share of total) for the year; 3) If either total or private employment is missing for an entire year, such that the private share for that year is unavailable, we impute the missing values based on the average share over the rolling window from two years prior to two years after the current year. This process imputes aggregate employment counts for nearly every case from 1978 onward. For the few remaining cases, mostly before 1978, we impute values by running a county-specific regression of the log of the employment measure (either total or total private) on year and quarter dummies from 1978 forward and replacing the missing values (including those from before 1978) with their predicted values from the regression.

A.3 Imputing Employment in County Business Patterns

When constructing the predicted log employment change as in Bartik (1991), we use County Business Patterns (CBP) data to measure local industry employment shares. In the relevant years, CBP data always report establishment counts by county, industry, and establishment size, but frequently suppress employment at the county by industry level. From 1974 forward, the establishment size groups are 1–4, 5–9, 10–19, 20–49, 50–99, 100–249, 250–499, 500–999, 1000–1499, 1500–2499, 2500–4999, and 5000 or more employees.

We impute employment at the county by industry level using establishment counts and nationwide information on employment by establishment size. For establishments with fewer than 1000 employees, we impute employment as the number of establishments times average pre-recession employment in the establishment size group, where the average comes from nationwide data across all industries. We use 1999 data to construct these imputation adjustments, but the results are very similar when using other years.
Nationwide CBP data report total employment among establishments with at least 1000 employees, but not by establishment size group. To impute employment for these large establishments, we assume that employment follows a log normal distribution, with mean $\mu$ and standard deviation $\sigma$, and estimate $(\mu, \sigma)$ using the generalized method of moments (GMM), as in Holmes and Stevens (2002) and Stuart (2022). We estimate $(\mu, \sigma)$ using the following four moments:

\begin{align*}
p_1 &= \Phi \left( \frac{\ln(1499) - \mu}{\sigma} \right) - \Phi \left( \frac{\ln(1000) - \mu}{\sigma} \right) \quad (A.1) \\
p_2 &= \Phi \left( \frac{\ln(2499) - \mu}{\sigma} \right) - \Phi \left( \frac{\ln(1500) - \mu}{\sigma} \right) \quad (A.2) \\
p_3 &= \Phi \left( \frac{\ln(4999) - \mu}{\sigma} \right) - \Phi \left( \frac{\ln(2500) - \mu}{\sigma} \right) \quad (A.3) \\
E[y] &= \exp(\mu + \sigma^2/2), \quad (A.4)
\end{align*}

where $p_1$ is the share of establishments of at least 1000 employees with 1000–1499 employees, $p_2$ is the share with 1500–2499 employees, $p_3$ is the share with 2500–4999 employees, $\Phi(\cdot)$ is the standard normal CDF, and $E[y]$ is average employment among establishments with at least 1000 employees.

We use equations (A.1)–(A.4) to estimate $(\mu, \sigma)$ with GMM, using the identity matrix as the weighting matrix. For years 1978, 1988, 1999, and 2006, the estimates of $(\mu, \sigma)$ are (7.50, 0.67), (7.49, 0.63), (7.50, 0.62), and (7.51, 0.67). We use 1999 parameters throughout for simplicity. Standard facts about the log-normal distribution imply that the imputed means for the four establishment size groups are (1249, 1950, 3373, 6679).

For 1999 and 2006, we can compare the county-industry employment imputations from this procedure (normalized by overall county employment to make industry shares) with those from the Upjohn Institute’s WholeData series (Bartik et al., 2019), which provides desuppressed employment counts in the NAICS period. The correlations are very high, in excess of 0.99, suggesting the imputation procedure is quite accurate.

\section*{B Results Appendix}

\section*{B.1 Robustness to Different Measures of Log Employment Changes}

Our baseline specification uses the change in log total wage and salary employment from BEAR to measure recession severity. We believe this variable is best because the BEA makes considerable efforts to construct data that are consistent over time, although this is more difficult for the self-employed (whose employment can vary over time in response to tax incentives). The two leading
alternatives are private wage and salary employment from BEAR and private wage and salary employment from QCEW.\footnote{CBP data represent another alternative, although its coverage is not quite as complete as BEAR or QCEW; notably, CBP excludes most public-sector employment, as well as agricultural services, railroads, postal workers, and private households.} Figures A.6–A.9 show that the estimated coefficients for employment, population, the employment-population ratio, and earnings per capita are quite similar when using these other measures to define recession severity. The similarity of the results is not surprising, as the public sector accounts for less than 25 percent of wage and salary employment on average, and BEAR data rely on QCEW data as an input. Still, it is reassuring that our results are not sensitive to this choice.

### B.2 Results Using Predicted Log Employment Changes

We estimate equation (1) using OLS. A potential concern with this approach is that employment changes in local areas might stem from factors besides recessions, such as changes in labor supply. A common approach in the literature—much of which examines ten-year employment changes rather than business-cycle peak-to-troughs—is to instead use variation in log employment changes predicted by a location’s baseline industrial structure, following Bartik (1991). In our setting, the predicted log employment change is

\[
b_i = \sum_j \eta_{i,j} (\ln(E_{j,t_1}) - \ln(E_{j,t_0})),
\]

where \(\eta_{i,j}\) is the share of employment in local area \(i\) in industry \(j\) in a base year, and the term in parentheses equals the nationwide log employment change in industry \(j\) from recession peak to trough. We use CBP data to construct \(\eta_{i,j}\) (see Appendix A.3) and QCEW data to construct the nationwide log employment change.\footnote{QCEW data have the advantage of being available at a quarterly frequency, which we could (but do not) use in constructing the predicted log employment change; our results are not sensitive to this choice. Because detailed county-by-industry employment counts in the QCEW are commonly suppressed, with less information with which to make imputations, we use the CBP to construct the pre-recession employment share.}

We do not use the predicted log employment change in our preferred specification, because our focus on a shorter window during recessions and our controls for pre-recession population growth mitigate concerns about labor supply driving the sharp employment changes that we see. Furthermore, recent work highlights issues that arise in using industry shift-share methods (Adão, Kolesár and Morales, 2019; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2021). Nonetheless, given the ubiquity of the Bartik (1991) approach, we report results from using it here.

Appendix Table A.1 describes the relationship between the actual log employment change and the predicted log employment change. The first column includes no other controls. For every recession besides 1990–1991, the predicted log employment change explains 33–36 percent of the cross-metro variation in the actual log employment change. For 1990–1991, the predicted log employment change explains only 7 percent of the actual variation. Columns 2 and 3 add in division fixed effects and controls for lagged population growth. The coefficients—which are all positive, as expected—are reasonably stable across specifications, especially after 1973–1975 when greater industry-level detail is available. Moreover, the coefficient estimates remain highly
Appendix Table A.2 shows that predicted log employment changes are more highly correlated across time than actual log employment changes. This is not surprising, as the shift-share variable primarily reflects local industry employment shares, which are relatively stable. These high correlations raise the concern that the coefficients on the predicted log employment change might not isolate the impact of a given recession. Instead, the predicted log employment change could pick up the effects of earlier or later recessions, in addition to secular changes in industry-level employment.

Appendix Figure A.10 displays estimates of how log employment varies with the predicted log employment change. The results are qualitatively similar to those using log employment changes in Figure 5 for the 1980–1982, 2001, and 2007–2009 recessions. There is less evidence of a persistent employment decline for the 1973–1975 and 1990–1991 recessions; for these recessions, there is clear evidence of an employment decline during the subsequent recession, consistent with the high cross-recession correlations. Figures A.11 through A.13 display results for population, the employment-population ratio, and earnings per capita. The patterns largely mirror those for employment.

B.3 The Post-Recession Evolution of Economic Activity in Commuting Zones

Our main approach defines local labor markets as metropolitan areas. Another reasonable approach is to use commuting zones, which span the entire (continental) United States, including rural areas. Appendix Figures A.14 through A.17 show that results are very similar when using commuting zones (specifically, the 2000 definition).

B.4 Back of Envelope Calculations on the Role for Productivity-Enhancing Reallocation

This appendix reports the results of simple calculations that assess whether recessions are likely to increase aggregate earnings per worker by reallocating employment to more productive areas. We refer to these calculations in the conclusion.

The change in aggregate earnings per worker due to recession-induced cross-area reallocation is

\[
Y_{t+k}^C - Y_t = \sum_i (\theta_{i,t+k}^C - \theta_{i,t}) Y_{i,t},
\]

where \(Y_t\) is aggregate earnings per worker in pre-recession year \(t\), and \(Y_{t+k}^C\) is the counterfactual level of earnings per worker in year \(t + k\) reflecting recession-induced employment reallocation.

---

\footnote{There is much less cross-sectional variation in predicted log employment changes than in actual log employment changes (Appendix Figure A.1); all else equal, this would cause the coefficients on the predicted log employment change to be larger than those on the actual log employment change. However, the predicted log employment change captures only a fraction of the total variation in log employment changes, so we would not necessarily expect the magnitudes to be identical even if we normalized by the standard deviations of the employment measures.}
across local labor markets. These aggregate earnings per worker terms are defined as:

\[ Y_t := \sum_i \theta_{i,t} Y_{i,t} \]  
(A.6)

\[ Y_{t+k}^C := \sum_i \theta_{i,t+k}^C Y_{i,t}, \]  
(A.7)

where \( Y_{i,t} \) is earnings per worker in metro \( i \) in year \( t \), \( \theta_{i,t} \equiv E_{i,t}/E_t \) is the employment share of metro \( i \) in year \( t \), and \( \theta_{i,t+k}^C \) is the counterfactual employment share in year \( t+k \). We construct this counterfactual employment share as

\[ \theta_{i,t+k}^C = \frac{E_{i,t} \times \exp(s_i \hat{\delta}_{t+k})}{\sum_j E_{j,t} \times \exp(s_j \hat{\delta}_{t+k})}. \]  
(A.8)

The numerator of this expression is the pre-recession employment level multiplied by the percent change in employment predicted by recession severity from equation (1). Using only the employment change that is explained by recession severity ensures that we do not attribute secular changes (absorbed by our controls) to the recession.

Column 1 of Appendix Table A.4 reports the unweighted standard deviation (SD) of the difference between the counterfactual employment share and the observed pre-recession employment share, \( (\theta_{i,t+k}^C - \theta_{i,t}) \). We construct this counterfactual 7–9 years after the recession trough, using the estimates in Panel A of Table 4. We set \( t \) as the peak recession year. Column 2 reports the unweighted SD of the relative employment share difference, \( (\theta_{i,t+k}^C - \theta_{i,t})/\theta_{i,t} \). There is a fair amount of reallocation, with the standard deviation ranging from 3.5 to 7.8 percent of baseline employment. Column 3 reports the nationwide average of mean annual earnings per worker in the peak year, expressed in constant 2019 dollars. Column 4 reports the change in aggregate earnings per worker, \( Y_{t+k}^C - Y_t \). In three out of five recessions, cross-area reallocation lowers earnings per worker. However, the aggregate changes are extremely small, ranging from a reduction of $224 (1990–1991) to an increase of $23 (1980–1982). This is underscored in column 5, which divides column 4 by column 3 and then multiplies by 100 to express percent changes. The largest change is only 0.3 percent of peak year earnings per worker.

To shed further light on these results, Appendix Figure A.21 displays the cross-metro correlations between the employment share change \( (\theta_{i,t+k}^C - \theta_{i,t}) \) and peak-year earnings per worker \( (Y_{i,t}) \). The marker symbols are proportional to the peak year employment share. High-earning metropolitan areas regularly lose and gain employment. On average, there is no net shift towards higher or lower earning metropolitan areas, as seen in Table A.4.

In sum, these calculations suggest that recessions do not meaningfully reallocate employment towards more productive metropolitan areas.
Table A.1: Cross-Sectional Relationship between Metropolitan Area Log Employment Change and Predicted Log Employment Change

<table>
<thead>
<tr>
<th>Panel</th>
<th>Predicted log employment change</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(0.177)</td>
<td>(0.199)</td>
<td>(0.209)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.355</td>
<td>0.466</td>
<td>0.498</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.162)</td>
<td>(0.141)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.362</td>
<td>0.593</td>
<td>0.667</td>
<td></td>
</tr>
<tr>
<td>Panel C: 1990–1991 Recession</td>
<td>1.394</td>
<td>0.777</td>
<td>1.090</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.234)</td>
<td>(0.228)</td>
<td>(0.231)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.067</td>
<td>0.428</td>
<td>0.493</td>
<td></td>
</tr>
<tr>
<td>Panel D: 2001 Recession</td>
<td>1.533</td>
<td>1.270</td>
<td>1.273</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.116)</td>
<td>(0.135)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.346</td>
<td>0.410</td>
<td>0.540</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.174)</td>
<td>(0.193)</td>
<td>(0.205)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.332</td>
<td>0.456</td>
<td>0.515</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Division fixed effects</th>
<th>x</th>
<th>x</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-recession population growth</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Table reports estimates of regressing the log employment change during recessions against the predicted log employment change during recessions, as in Bartik (1991). There are 358 metropolitan areas in the sample. Heteroskedastic-robust standard errors are in parentheses.
Source: Authors’ calculations using BEAR, CBP, QCEW, and SEER data.
Table A.2: Correlation of Metropolitan Area Predicted Log Employment Changes

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Unadjusted</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973–75</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980–82</td>
<td>0.813</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990–91</td>
<td>0.722</td>
<td>0.724</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td>0.721</td>
<td>0.696</td>
<td>0.809</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>2007–09</td>
<td>0.473</td>
<td>0.525</td>
<td>0.724</td>
<td>0.667</td>
<td>1.000</td>
</tr>
<tr>
<td><strong>Panel B: Adjusted for Census division</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973–75</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980–82</td>
<td>0.758</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990–91</td>
<td>0.667</td>
<td>0.662</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td>0.661</td>
<td>0.629</td>
<td>0.811</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>2007–09</td>
<td>0.496</td>
<td>0.498</td>
<td>0.737</td>
<td>0.686</td>
<td>1.000</td>
</tr>
<tr>
<td><strong>Panel C: Adjusted for Census division and pre-recession population growth</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973–75</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980–82</td>
<td>0.740</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990–91</td>
<td>0.595</td>
<td>0.577</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td>0.556</td>
<td>0.535</td>
<td>0.716</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>2007–09</td>
<td>0.434</td>
<td>0.453</td>
<td>0.673</td>
<td>0.611</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Notes: Table reports correlations of predicted log employment changes (Bartik, 1991) across recessions for 358 metropolitan areas. Panel B reports correlations after partialling out Census division fixed effects, and Panel C partials out Census division fixed effects and pre-recession population growth.
Source: Authors’ calculations using BEAR, CBP, and QCEW data.
### Table A.3: Bias in Vector Autoregression Parameters

<table>
<thead>
<tr>
<th>Truth</th>
<th>$\hat{\alpha}_{11}$</th>
<th>$\hat{\alpha}_{12}$</th>
<th>$\hat{\alpha}_{21}$</th>
<th>$\hat{\alpha}_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>0.000</td>
<td>0.750</td>
<td>1.000</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time series obs. ($T$)</th>
<th>Average estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>$-0.038$ $-0.101$ $0.701$ $0.855$</td>
</tr>
<tr>
<td>25</td>
<td>$-0.022$ $-0.060$ $0.725$ $0.918$</td>
</tr>
<tr>
<td>50</td>
<td>$-0.010$ $-0.030$ $0.741$ $0.960$</td>
</tr>
<tr>
<td>100</td>
<td>$-0.004$ $-0.015$ $0.749$ $0.980$</td>
</tr>
<tr>
<td>500</td>
<td>$-0.001$ $-0.003$ $0.756$ $0.996$</td>
</tr>
<tr>
<td>5000</td>
<td>0.000 0.000 0.762 1.000</td>
</tr>
</tbody>
</table>

Notes: Table displays average estimates of parameters in equations (7)–(8). We simulate data following equations (12)–(14). We set $e_{i,0} \sim N(13.94,1.00^2)$, $p_{i,0} \sim N(14.49,1.02^2)$, $\varepsilon_{i,e,t} \sim N(0,0.015^2)$, $\varepsilon_{i,p,t} \sim N(0,0.015^2)$, $\phi = 0.75$, and $N = 50$. Results are based on 499 Monte Carlo simulations.
Table A.4: Changes in Earnings per Worker due to Recession-Induced Reallocation

<table>
<thead>
<tr>
<th>Recession</th>
<th>SD, emp. share change</th>
<th>SD, rel. emp. share change</th>
<th>Mean earnings per worker, peak year</th>
<th>Change in mean earnings per worker</th>
<th>Percent change in mean earnings per worker (× 100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973–1975</td>
<td>0.00038</td>
<td>0.073</td>
<td>56,131</td>
<td>−12</td>
<td>−0.021</td>
</tr>
<tr>
<td>1979–1982</td>
<td>0.00035</td>
<td>0.078</td>
<td>56,425</td>
<td>23</td>
<td>0.041</td>
</tr>
<tr>
<td>1989–1991</td>
<td>0.00049</td>
<td>0.072</td>
<td>65,394</td>
<td>−224</td>
<td>−0.343</td>
</tr>
<tr>
<td>2000–2002</td>
<td>0.00020</td>
<td>0.049</td>
<td>79,945</td>
<td>−71</td>
<td>−0.088</td>
</tr>
<tr>
<td>2007–2009</td>
<td>0.00017</td>
<td>0.035</td>
<td>88,751</td>
<td>3</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Notes: Column 1 reports the unweighted standard deviation of the difference between the counterfactual employment share (reflecting recession-induced employment reallocation) and the observed pre-recession employment share, \((\theta_{C,t+k} - \theta_{t,t})\). We construct this counterfactual 7–9 years after the recession trough, using the estimates in Panel A of Table 4. Column 2 reports the unweighted SD of the relative employment share change, \((\theta_{C,t+k} - \theta_{t,t})/\theta_{t,t}\). Column 4 reports the change in aggregate earnings per worker, \(Y_{t+k} - Y_t = \sum_i (\theta_{C,i,t+k} - \theta_{i,t})Y_{i,t}\). Column 5 divides column 4 by column 3 and then multiplies by 100 to express percent changes.

Source: Authors’ calculations using BEAR, decennial census, and ACS data.
Figure A.1: Density of Log Employment Changes and Predicted Log Employment Changes During Recessions Across Metros

(a) Log Employment Change, Demeaned

(b) Log Employment Change

(c) Predicted Log Employment Change, Demeaned

Notes: Figure shows estimated kernel densities of the log wage and salary employment change (Panels A and B) and predicted log employment change based on pre-recession industrial structure (as in Bartik (1991); Panel C) across metros for each of the five recessions since the mid 1970s. In Panels A and C, log employment changes are demeaned for each recession using the unweighted average across metros. There are 358 metropolitan areas in the sample. Source: Authors’ calculations from BEAR, CBP, and QCEW data.
Figure A.2: The Evolution of Metropolitan Area Log Employment from County Business Patterns and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log employment from CBP data. See notes to Figure 5. Source: Authors’ calculations using CBP, BEAR, and SEER data.
Figure A.3: The Evolution of Metropolitan Area Log Establishments and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log establishments from CBP data. See notes to Figure 5.
Source: Authors’ calculations using CBP, BEAR, and SEER data.
Figure A.4: The Evolution of Metropolitan Area Log Real Per Capita Earnings and Changes in Log Employment During Recessions, Robustness to Different Earnings Measures

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variables are log real earnings per capita (age 15+), either by place of work or place of residence, as indicated in the legend. For comparability, both measures exclude contributions to government social insurance but include proprietors’ income; this is distinct from the earnings measure in Figure 9, which excludes proprietors’ income. (Proprietors’ income is separable from earnings by place of work but not place of residence). There are 358 metropolitan areas in the sample. Source: Authors’ calculations using BEAR and SEER data.
Figure A.5: The Evolution of Metropolitan Area Log Real Per Worker Earnings and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log real earnings per wage and salary worker. See notes to Figure 5. Source: Authors’ calculations using BEAR and SEER data.
Figure A.6: The Evolution of Metropolitan Area Log Employment and Changes in Log Employment During Recessions, Robustness to Different Log Employment Change Measures

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log wage and salary employment from BEAR data, and the key independent variable is indicated in the legend. For independent variables besides BEA wage/salary employment, we normalize the coefficients by multiplying point estimates by the ratio of the standard deviation of the independent variable to the standard deviation of the BEA wage/salary log employment change. There are 358 metropolitan areas in the sample.

Source: Authors’ calculations using BEAR, QCEW, and SEER data.
Figure A.7: The Evolution of Metropolitan Area Log Population Age 15+ and Changes in Log Employment During Recessions, Robustness to Different Log Employment Change Measures

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log population age 15 and above, and the key independent variable is indicated in the legend. See notes to Figure A.6.
Source: Authors’ calculations using BEAR, QCEW, and SEER data.
Figure A.8: The Evolution of the Metropolitan Area Log Employment-Population Ratio and Changes in Log Employment During Recessions, Robustness to Different Log Employment Change Measures

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log of the ratio of wage and salary employment to population age 15 and above, and the key independent variable is indicated in the legend. See notes to Figure A.6.
Source: Authors’ calculations using BEAR, QCEW, and SEER data.
Figure A.9: The Evolution of Metropolitan Area Log Real Per Capita Earnings and Changes in Log Employment During Recessions, Robustness to Different Log Employment Change Measures

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log real earnings per capita (age 15+), and the key independent variable is indicated in the legend. See notes to Figure A.6. Source: Authors’ calculations using BEAR, QCEW, and SEER data.
Figure A.10: The Evolution of Metropolitan Area Log Employment and Predicted Changes in Log Employment During Recessions

(a) 1973–1975 Recession
(b) 1980–1982 Recession
(c) 1990–1991 Recession
(d) 2001 Recession
(e) 2007–2009 Recession
(f)

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log wage and salary employment from BEAR data, and the key independent variable is the predicted log employment change as in Bartik (1991). Specifications are indicated by the legend. See notes to Figure 5.
Source: Authors’ calculations using BEAR, CBP, and QCEW data.
Figure A.11: The Evolution of Metropolitan Area Log Population Age 15+ and Predicted Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log population age 15 and above. See notes to Figure A.10.
Sources: Authors' calculations using BEAR, CBP, QCEW, and SEER data.
Figure A.12: The Evolution of the Metropolitan Area Log Employment-Population Ratio and Predicted Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log of the ratio of wage and salary employment to population age 15 and above. See notes to Figure A.10.
Source: Authors’ calculations using BEAR, CBP, QCEW, and SEER data.
Figure A.13: The Evolution of Metropolitan Area Log Real Per Capita Earnings and Predicted Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log real earnings per capita (age 15+). See notes to Figure A.10.
Source: Authors’ calculations using BEAR, CBP, QCEW, and SEER data.
Figure A.14: The Evolution of Commuting Zone Log Employment and Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log wage and salary employment from BEAR data. There are 691 CZs in the sample. Standard errors are clustered by commuting zone. See notes to Figure 5.

Source: Authors’ calculations using BEAR and SEER data.
Figure A.15: The Evolution of Commuting Zone Log Population Age 15+ and Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log population age 15 and above. See notes to Figure A.14.
Source: Authors’ calculations using BEAR, SEER, and QCEW data.
Figure A.16: The Evolution of the Commuting Zone Log Employment-Population Ratio and Changes in Log Employment During Recessions

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

(f)

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log of the ratio of wage and salary employment to population age 15 and above. See notes to Figure A.14.
Source: Authors’ calculations using BEAR and SEER data.
Figure A.17: The Evolution of Commuting Zone Log Real Per Capita Earnings and Changes in Log Employment During Recessions

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log real earnings per capita (age 15+). See notes to Figure A.14. Source: Authors’ calculations using BEAR and SEER data.
Figure A.18: The Evolution of the Metropolitan Area Log Employment-Population Ratio and Changes in Log Employment During Recessions, Role of Shifts in Age Composition

Notes: The solid blue line displays estimates of equation (1), separately for each recession, where the dependent variable is the log of the ratio of wage and salary employment to population age 15 and above. The line in red circles is the predicted change in the log employment-population due to post-recession changes in the age structure; we estimate this predicted change as the product of estimates of event study variants of equation (1)—where the dependent variables are the share of population age 15–39, 40–64, and over 65, and all regressions control for all of these shares as of year $t_0 - 2$ to ensure an exact decomposition—and estimates of the cross-sectional, pre-recession relationship between the log employment-population ratio and these age shares. See notes to Figure 5.

Source: Authors’ calculations using BEAR and SEER data.
Figure A.19: The Evolution of Metropolitan Area Log Employment and Changes in Log Employment During Recessions, Longer Horizon

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is log wage and salary employment from BEAR data. See notes to Figure 5, which reports estimates over a shorter time horizon. Source: Authors’ calculations using BEAR and SEER data.
Figure A.20: The Evolution of the Metropolitan Area Log Employment-Population Ratio and Changes in Log Employment During Recessions, Longer Horizon

Notes: Figure reports estimates of equation (1), separately for each recession. The dependent variable is the log ratio of wage and salary employment to population age 15 and above. See notes to Figure 8, which reports estimates over a shorter time horizon.

Source: Authors’ calculations using BEAR and SEER data.
Figure A.21: Correlation between Reallocation-Induced Change in Employment Share and Peak Year Earnings per Worker

(a) 1973–1975 Recession

(b) 1980–1982 Recession

(c) 1990–1991 Recession

(d) 2001 Recession

(e) 2007–2009 Recession

Notes: Change in metro employment share is the employment share under the counterfactual minus the employment share in the peak recession year. Marker size is proportional to peak year employment share. Unweighted and peak-year-employment-share weighted correlations are reported. See notes to Appendix Table A.4.
Source: Authors’ calculations using BEAR and SEER data.