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WHERE HAVE ALL THE GOOD JOBS GONE?
CHANGES IN THE GEOGRAPHY
OF WORK IN THE US, 1980-2021

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ABSTRACT

We examine changes in the spatial distribution of good jobs across US commuting zones over 1980-2000 and 2000-2021. We define good jobs as those in industries in which full-time workers attain high wages, accounting for individual and regional characteristics. The share of good jobs in manufacturing has plummeted; for college graduates, good jobs have shifted to (mostly tradable) business, professional, and IT services, while for those without a BA they have shifted to (non-tradable) construction. There is strong persistence in where good jobs are located. Over the last four decades, places with larger concentrations of good job industries have tended to hold onto them, consistent with a model of proportional growth. Turning to regional specialization in good job industries, we find evidence of mean reversion. Commuting zones with larger initial concentrations of good jobs have thus seen even faster growth in lower-wage (and mostly non-tradable) services. Changing regional employment patterns are most pronounced among racial minorities and the foreign-born, who are relatively concentrated in fast growing cities of the South and West. Therefore, good job regions today look vastly different than in 1980: they are more centered around human-capital-intensive tradable services, are surrounded by larger concentrations of low-wage, non-tradable industries, and are more demographically diverse.

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1 Introduction

In recent decades, local labor markets in the United States have undergone a series of seismic shifts. Notable among these are the increased concentration of highly educated workers in large cities, driven by the elevated labor productivity, innovation prospects, and amenities these locations afford (Moretti, 2004a, 2021; Diamond, 2016; Davis and Dingel, 2019); and the loss of manufacturing jobs in former industrial regions, caused by automation (Autor et al., 2013b; Acemoglu and Restrepo, 2020), globalization (Autor et al., 2013a) and broader secular movements (Charles et al., 2019). The creation of high-paying professional-service jobs, primarily for college workers, in one set of places, and the destruction of high-paying industrial jobs, primarily among non-college workers, in another set of places have widened regional disparities in earnings and employment rates (Amior and Manning, 2018; Austin et al., 2018; Gaubert et al., 2021). To examine the long-run consequences of these adjustments, we consider how the spatial distribution of good jobs in the United States evolved over the last two decades of the 20^{th} century, when the pace of technical change accelerated, and the first two decades of the 21^{st} century, when manufacturing decline intensified.

The well-documented clustering of firms in high-tech industries (e.g., Moretti, 2012; Kerr and Robert-Nicoud, 2020) and rise of superstar cities (e.g., Florida, 2003; Gyourko et al., 2013) may seem to suggest we already know how the location of good jobs has changed: high-paying work must have become even more concentrated in already successful places. But recent literature adds nuance to the story, raising ambiguity about how the geography of opportunity is evolving. On the one hand, superstar cities have seen rising incomes collide with inelastic housing supply, constraining local employment from expanding in concert with local productivity (Saiz, 2010; Hsieh and Moretti, 2019), and raise demand for non-traded services, possibly crowding out workers in some tradable sectors (Albert and Monras, 2022; Couture et al., 2024). As a result, second-tier cities, such as Austin and Denver, are pulling good jobs out of first-tier cities, such as New York and San Francisco, possibly expanding access to economic opportunity.[1] On the other hand, weakening labor mobility in response to adverse shocks (Dao et al., 2017; Ganong and Shoag, 2017), especially among non-college workers (Bound and Holzer, 2000; Autor et al., 2019), may have narrowed access to good jobs. Because places exposed to deindustrialization may lack the human capital needed to expand into knowledge-intensive sectors (Gagliardi et al., 2023; Howard et al., 2024), workers tied to these locations may have seen their employment options diminish (Zabek, 2024). In exploring how the location of good jobs has changed, we reflect on recent research regarding economic restructuring in US local labor markets.

[1] See, e.g., Muro and You (2023).

By "good jobs" we mean employment in industries that pay a positive wage premium relative to other sectors, accounting for individual and regional characteristics. Most of the existing literature on geographical differences in economic opportunities has focused on spatial differences in wages or income. By contrast, we focus on spatial differences in the location of industries that pay high wages.

The concept of a good job has a long history in economics.[2] It was prominent in early labor literature, including the study of industrial relations systems (Dunlop, 1958), dual labor markets (Doeringer and Piore, 1971), unions (Freeman and Medoff, 1984), and compensating earnings differentials (Rosen, 1986).[3] A first generation of empirical literature debated whether interindustry wage differentials represented true wage premia—due, e.g., to efficiency wages (Krueger and Summers, 1988)—or were instead the byproduct of workers with high unmeasured earnings potential selecting into certain sectors (Murphy and Topel, 1990). Modern empirical approaches, which use longitudinal data on workers and firms to account for worker self-selection, provide strong support for the existence of industry wage premia (Abowd et al., 1999). High-wage industries are ones disproportionately populated by high-wage firms (Card et al., 2018; Freund, 2022), in which workers moving in (from lower-premium industries) and workers moving out (to lower-premium industries) experience changes in earnings of similar absolute magnitudes and of opposite sign (Card et al., 2024). Whatever their origin, mobility into good jobs has been a channel for less-educated workers to attain middle class incomes (Haltiwanger et al., 2018) and the creation of good jobs is increasingly seen as a goal of public policy (Rodrik and Sabel, 2019). The relocation of good jobs thus indicates how the geography of opportunity is changing.

In our analysis, we use cross-sectional data from the Census and American Community Survey to study shifts in the location of good jobs across U.S. commuting zones (CZs). We apply a Mincer wage equation to estimate industry earnings premia and define good jobs as those in industries in the top tercile of estimated industry fixed effects. Since these fixed effects could be contaminated by worker selection into jobs, we verify that our estimates for 2000 to 2021 closely track those obtained by Card et al. (2024), who estimate industry effects by applying an AKM model (Abowd et al., 1999) to longitudinal data from the LEHD

[2]In the popular imagination, a good job is often associated with a level of pay that allows a worker to own a home, take regular vacations, send their kids to college, and retire comfortably. The idea appears to have drawn inspiration from business, culture, and politics, including the $5-a-day wage Henry Ford began offering workers in his auto factories in 1914, the notion of the "American Dream" popularized by James Truslow Adams (1931), and passage of the National Labor Relations Act (1935), which expanded rights for collective bargaining, and the Fair Labor Standards Act (1938), which created a federal minimum wage.

[3]Appendix Figure A1 shows the share of publications that mention "good jobs", and, for comparison, "local labor markets," from 1880 to the present based on Google Ngram. Usage of "good jobs" began in the early 1900s. It peaked in the early 1940s, when the US labor movement was expanding rapidly, and again in the 2000s, when manufacturing job losses became salient in academic research and public policy discussions.

for 2008 to 2019. Since their model conditions on worker fixed effects, it appears that our industry ranking of good jobs are not severely biased by worker sorting across industries.[4]

Studying local labor markets is motivated in part by the strong observed connection between material well-being and place (Chyn and Katz, 2021). Evidence of such place effects has heightened interest in the nature of geographic labor mobility. The less mobile labor is geographically—i.e., the steeper are local labor supply curves—the more adjustment to labor demand shocks will occur through changes in local wages and employment rates and the less through regional population flows (Moretti, 2011). Earlier optimism that labor in the United States was sufficiently geographically mobile for regional economies to equilibrate rapidly to shocks, with workers readily moving to opportunity (Greenwood and Hunt, 1984; Blanchard et al., 1992), has given way to pessimism about the speed of labor market adjustment (Bound and Holzer, 2000; Dao et al., 2017; Olney and Thompson, 2024). Local labor markets exposed to adverse shocks tend to see earnings and employment rates remain depressed for a decade or more (Amior and Manning, 2018; Autor et al., 2022). The implied upward slope to local labor supply curves may arise from a combination of costly migration and worker heterogeneity in preferences over regions (e.g., Eckert and Peters 2022; Caliendo et al. 2019; Allen and Donaldson 2020; Howard 2020; Galle et al. 2023), although the literature is just beginning to provide direct evidence of this mechanism (Zabek, 2024).

Sluggish geographic labor mobility in response to shocks does not necessarily mean that barriers to mobility are high. Adjustments in local housing markets may dampen incentives for labor flows between regions. In particular, the durable nature of housing may create a kink in housing supply curves at the initial equilibrium price (Glaeser and Gyourko, 2005, 2018), with housing supply more inelastic below this price and more elastic above it. Local housing prices may then be strongly responsive downward to any reduction in housing demand. If an adverse labor demand shock caused nominal earnings to fall in a region, the resulting decline in housing prices—and attendant decline in the price of non-traded goods—could leave real wages comparatively unchanged, thereby reducing pressures for out-migration (Notowidigdo, 2020). Real wages vary much less across local labor markets than do nominal wages (Moretti, 2013; Diamond and Moretti, 2021), which is consistent with variation in housing prices helping maintain spatial equilibrium. However, the documented responsiveness of employment rates to adverse local shocks is suggestive of changes in the real return to working, which may indicate that changes in real wages are central to the adjustment process (Amior and Manning, 2018; Kim and Vogel, 2021).[5]

[4]We caution, however, that we cannot replicate this validation exercise for the period 1980-2000, when industry effects from AKM models are not available due to a lack of comparable longitudinal data.

[5]Also on housing and migration, see Howard (2020) and Bernstein and Struyven (2022).

The four decades that makeup our period of analysis include momentous changes in which industries are the main sources of good jobs for the US labor market. By construction, changes in the importanace of an industry as a source of good jobs in the US depend on changes in its overall size and changes in its conditional mean wage. We find that between 1980 and 2021, the share of good jobs held by workers in manufacturing dropped sharply. At the same time, the share manufacturing jobs we classify as good jobs was stable; despite the sector shrinking, the likelihood that manufacturing jobs still pay well (conditional on worker observables) has changed little. By contrast, human capital-intensive services—finance, real estate, professional services, legal services, and information technology—experienced a tripling in their share of good jobs—both because employment in the sector expanded and because within the sector job growth was stronger in high premium industries.

Our analysis proceeds in three steps. We first ask how the *concentration* of good jobs in US commuting zones (CZs) has evolved over time. An active literature considers how the transition from manufacturing to services has affected the spatial distribution of occupations (Michaels et al., 2019; Rossi-Hansberg et al., 2019) and business functions (Duranton and Puga, 2005; Kleinman, 2022; Jiang, 2023).[6] In tracking how CZs move up and down the distribution of high-wage employment, we identify which types of places have succeeded in creating more good jobs on net, regardless of whether these positions are in manufacturing, energy, banking, or software. One possibility is that good jobs begin concentrated in larger cities and then diffuse spatially, as in the innovation model of Duranton and Puga (2001); alternatively, agglomeration effects may create momentum in the location of good jobs (Ellison and Glaeser, 1999; Greenstone et al., 2010; Moretti, 2012, 2021; Diamond, 2016; Davis and Dingel, 2019), such that their concentration in industry clusters intensifies over time.

Unsurprisingly, we find that employment growth in good jobs has been strongest in CZs that were initially least specialized in manufacturing and weakest in CZs that were initially most specialized in manufacturing (Gagliardi et al., 2023). Yet, because this pattern holds throughout the size distribution, the churning we document—with service-oriented CZs overtaking manufacturing-oriented CZs within each size decile—is consistent with persistence in CZ employment in good jobs. Over 1980 to 2000, CZ employment in good jobs (as a share of national employment) is close to a random walk (Gabaix, 1999)—i.e., there is neither regional convergence nor divergence—while over 2000 to 2021, there is mild divergence (i.e., momentum) in the location of good jobs. Whereas average incomes have diverged strongly across US regions since 1980 (Ganong and Shoag, 2017; Gaubert et al., 2021), regional employment in good jobs has remained comparatively stable. Having a larger initial concentration of

[6]See Kim (1995), Klein and Crafts (2012), Michaels et al. (2012), and Eckert and Peters (2022) for historical evidence on the shift from agriculture to manufacturing across US regions.

good jobs strongly predicts having more good jobs in subsequent decades.

Next, we examine the evolution of CZ *specialization* in good jobs, defined as the share of CZ employment in good jobs relative to the national share of employment in these industries. Regional specialization in good jobs may evolve differently from regional concentration in good jobs if, e.g., preferences for non-traded goods are non-homothetic (Couture et al., 2024), such that rising local incomes (possibly associated with the disproportionate local presence good jobs) create demand effects that lead to rising shares of employment in non-traded services. Existing evidence on the stability of US regional specialization patterns is mixed. Although industries appear to relocate across US metropolitan areas at high frequency (Duranton, 2007), industry specialization patterns for US states appear to be stable over long time spans (Morris-Levenson, 2022). We find clear evidence of regional convergence in specialization in good jobs, as indicated by mean reversion, which is modestly weaker for the 2000-2021 period than for the 1980-2000 period. Despite persistence in the location of good jobs, CZs initially more specialized in them have seen employment in other types of work expand more rapidly. Geographic diffusion of specialization in good jobs is stronger still for specific subgroups of workers, including racial minorities and the foreign-born, consistent with these groups having better access to good jobs being created in second-tier US cities in the South and West (Kahn et al., 2022). Although good jobs remain concentrated in successful CZs, the unconditional likelihood of landing a good job has risen differentially in CZs that initially were lower down the specialization ranking.

As a final exercise, we ask which observable characteristics of localities are correlated with the probability of moving up or down the distribution of good jobs. We focus on 54 variables in eight broad categories that existing literature identifies as potential shifters of labor demand or supply: the CZ's size and demographics; its human capital; its industry structure; state taxes and regulations; the CZ's local public sector; local amenities; the structure and fragmentation of local governments; and proxies for social capital. Our findings are not always in line with the existing literature or with our priors; we caution that our estimates cannot be considered causal and should be interpreted as suggestive at best. Yet, it is still striking that most of the usual suspects one would select as correlates of regional growth in good jobs fail to make an appearance.

The changing location of good jobs has potentially important implications for our understanding of regional economic performance. A growing body of evidence identifies policy-induced supply constraints as important factors in lowering housing supply elasticities and raising housing costs in some cities (Glaeser and Gyourko, 2018; Gyourko and Krimmel, 2021). Since many high-paying jobs have agglomerated in cities with inelastic housing supply, stringent land use regulations may have reduced the number of U.S. workers who have access to good jobs (Hsieh and Moretti, 2019) and contributed to greater wage and income inequality (Autor, 2019). Widening regional disparities in labor market outcomes have increased interest in using place-based policy to expand employment in economically distressed regions (Austin et al., 2018; Bartik, 2020; Fajgelbaum and Gaubert, 2020; Bilal, 2023).

More broadly, the changing geography of good jobs matters for our understanding of the ultimate effects of shifts in labor demand induced by globalization and technological change over the last four decades. Whereas the 1980s was a decade characterized by a strong skill-biased technical change but limited trade with the developing world (Freeman, 1995), the 2000s were characterized by a sharp increase in trade with low-wage countries, especially China (Autor et al., 2016). Technology-induced job gains may have occurred at the wrong time and in the wrong places to offset job loss in manufacturing (Autor et al., 2015; Gagliardi et al., 2023). The changing location of good jobs may also inform our understanding of the consequences of the secular decline in spatial mobility of US workers, especially those without a college degree. If shocks to labor demand are spatially concentrated, mobile labor could in principle help in absorbing the shocks with limited employment effects (Blanchard et al., 1992). However if workers are not very mobile or their mobility is not directed toward stronger local economies (Yagan, 2019), then labor demand shocks to specific regions may have more painful and more enduring consequences.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the data, our definition of good jobs and our two main outcome variables. Sections 4 and 5 present our main empirical findings. Section 6 concludes.

2 Definition and Measurement of Good Jobs

In this section, we describe how we quantify employment in good jobs. We start by describing the data and our geographical unit of analysis. We then discuss how we define and empirically measure employment in good jobs, and address potential sources of bias in our measure.

2.1 Data

Our main data sources are the 5% samples of the 1980, 1990, and 2000 US Census and the five-year combined 1% samples of the American Community Survey (ACS) for 2008 to 2012 (which we designate as 2010) and 2017 to 2021 (which we designate as 2021).[7]

Local Labor Markets. To examine changes in the spatial distribution of good jobs, we use data on earnings and employment for US Commuting Zones (Tolbert and Sizer, 1996;

[7] See Dustmann et al. (2023) on identification issues when studying labor market adjustment using data from repeated cross sections.

Dorn, 2009). A sizable recent literature examines how local labor markets adjust to labor demand shocks arising from changes in technology, product market competition, government regulation, and other sources.[8] Less is known about attendant changes in regional specialization. Our study of the evolving location of good jobs widens the focus from transitional adjustment to shocks to long-run changes in the sectoral orientation of places.

Commuting zones—as adjoining counties within which individuals tend to both live and work—represent a behavioral concept of local labor markets.[9] Other commonly used concepts include Metropolitan Statistical Areas (MSAs), which are sets of adjoining counties that include at least one an urban area with 50,000 or more residents, and Public Use Micro-data Areas (PUMAs), which are sets of adjoining counties and Census Tracts with a population of at least 100,000 residents, that lie within a state, and that broadly follow city or town administrative boundaries.[10] Relative to MSAs, CZs cover the entire nation, rather than just urbanized counties; relative to PUMAs, CZs are based on revealed preference in employment and residential choice, rather than potentially arbitrary jurisdictional boundaries. In practice, however, differences in empirical results emanating from these alternative market concepts are likely to be slight. Because non-urban areas account for a small share of the U.S. population, empirical analysis that weights regions by local employment or population size, as is common practice, would tend to put CZs, MSAs, and PUMAs on similar footing. What may matter more for our understanding of local labor markets is accounting for variation in the micro-geography of housing supply (e.g., Baum-Snow and Han 2024) or ease of transport within and between regions (e.g., Akbar et al. 2023), either of which could create geographic variation in the slope of local labor supply curves.

In defining local labor markets, one implicitly specifies the boundaries at which there are spatial breaks in the strength of economic linkages between agents. Recent work evaluates the nature of these breaks. In their analysis of the spatial dimensions of job search in the UK, Manning and Petrongolo (2017) find that few workers would likely be attracted to jobs more than 5km from their current location, suggesting local labor markets are in fact very local. Yet, because longer distance search and matching do occur, there appears to be substantial geographic overlap in these markets, which is not countenanced by the hard boundaries used to delineate CZs and related market concepts. Other evidence of the permeability of local

[8]See Autor et al. (2024) and Acemoglu et al. (2024) for discussions of this body of work.

[9]In the European Union, the common use of the Nomenclature for Units of Territorial Statistics (NUTS) to define regional economies relies on administrative boundaries, rather than commuting behavior. Functional Urban Areas are a variant of CZs that have been applied to OECD and EU countries (Dijkstra et al., 2019).

[10]CZs and PUMAs are defined by the US Census Bureau and updated periodically. The most commonly used definition of CZs is that based on 1990 commuting patterns, although CZ definitions have been updated using 2010 data (Fowler and Jensen, 2020). MSAs and other Core Based Statistical Areas, including Micropolitan Statistical Areas, are defined by the US Office of Management and Budget (OMB, 2021).

labor market boundaries comes from commuting between CZs (Monte et al., 2018). Variation in the openness of local labor markets to commuting—due, e.g., to differences in geography or transportation infrastructure—may create heterogeneity in how CZs respond to localized shocks. The common empirical approach of estimating average regional impact effects would tend to suppress any such heterogeneity. Bartik (2024) proposes using the estimated of strength regional spillovers as an alternative basis for defining local labor markets.

Workers. In the empirical analysis, we limit the sample to full-time workers (those who work at least 30 hours per week and 40 weeks per year) of prime age (those ages 25 to 54 years) in the civilian economy (excluding those in the military and national security sectors) who do not reside in group quarters.[11] Focusing on full-time workers is helpful for interpreting the wage regressions we estimate, since among this group earnings are likely to vary more due to differences in hourly or weekly wages than due to differences in hours worked, which allows us to obtain more reliable estimates of industry wage premia.[12]

Appendix Table A1 reports summary statistics for workers in our sample. Our study period encompasses profound changes in the composition of the US labor force. As is well known, the share of women and college-educated workers increased sharply between 1980 and 2021; the former rose from 35.8% to 45.0%, while the latter jumped even more in proportional terms, from 12.3% to 26.2%. In addition, the shares of foreign-born and Asian workers tripled in this period, while the share of Hispanic workers quadrupled. By contrast, the share of non-Hispanic white workers declined, from 82.5% to 59.3%. The share of workers employed in manufacturing fell precipitously, from 28.0% to 11.9%. Because workers are unevenly distributed across regional economies by education, race, and sector, these national shifts imply much larger shifts at the local level.

In tracking the changing location of good jobs, we first examine all full-time workers, then consider workers separately by education level, and finally further distinguish workers by gender, nativity, and race. When we fully separate workers along these dimensions, very small CZs tend to have zero-sized employment cells. To remedy, we exclude the 240 CZs with fewer than 52,000 residents in 2000, which together represented 1.9% of the US population and 1.9% of US employment in that year, as seen in Table A2. This leaves us with 499 CZs.

[11] We further limit the sample to individuals who report annual earnings in excess of the equivalent federal minimum wage for a full-time worker. See Table A1 for details.

[12] This focus precludes us from considering recent developments in the labor market of low-wage workers. Along with rising joblessness in distressed regions, there has been an increase in the precarity of work, which takes the form of frequent changes in work schedules, difficulty in obtaining sufficient work hours to qualify for full-time employment benefits, and financial insecurity (Kalleberg, 2009; Schneider and Harknett, 2019). Deteriorating conditions for low-wage workers may be due in part to displacement of traditional, mom-and-pop retailers with supercenters, such as Walmart (Neumark et al., 2008; Dube et al., 2022). Much of the rise in earnings inequality, for instance, appears to be due to the widening spread between high-paying firms in tech industries and low-paying firms in retail sectors (Haltiwanger et al., 2022).

While the exclusion of small CZs is immaterial for our regression results, it greatly improves the graphical exposition of our findings.

2.2 Defining Good Jobs

We define good jobs as those in industries in which full-time, full-year workers attain high earnings, conditional on their education, labor-market experience, and demographic characteristics. Evidence of large wage differences between industries appeared early in research by labor economists (Dunlop, 1958) and has since inspired a large body of literature (Groshen, 1991). Efforts to account for interindustry earnings differences have led to significant advances in our understanding the role of unmeasured ability in worker outcomes (e.g., Murphy and Topel, 1990), the self-selection of workers into particular jobs (e.g., Oster, 2019), and how to interpret regional earnings differentials (e.g., Topel, 1986). We have since learned that increased dispersion in earnings between industries is a dominant factor behind the recent rise in US earnings equality (Haltiwanger et al., 2023). Since industries tend to agglomerate spatially, this finding would seem to imply that there should have been a corresponding increase in the geographic dispersion of access to good jobs.

Our definition of good jobs is based on estimating the following Mincer wage regression across workers j, employed in industries i, in year t:

$$\ln W_{jt} = \beta ED_{jt} + \delta EXP_{jt} + \gamma ED_{jt} \cdot EXP_{jt} + \theta X_{jt} + \alpha_{i(j)t} + \epsilon_{jt} \tag{1}$$

where W_j is annual earnings; ED_j includes identifiers for the highest level of education attained (high school, some college, college, post-graduate); EXP_j is a quartic in potential work experience (age minus standard age of school exit for highest level of attainment); X_i includes identifiers for gender, race (white, Black, Native American, Asian, other), Hispanic ethnicity, and birth region (Latin America/Caribbean, Europe, Asia, other); and $\alpha_{i(j)}$ is a fixed effect for worker j's industry. We estimate equation (1) separately by year, first as a single regression for all full-time, prime-age workers, which allows us to characterize how the overall spatial distribution of good jobs has evolved over time, and then separately for workers grouped by gender and college attainment, which allows us to track the geographic dimensions of differences in outcomes for college and non-college workers and whether these differences in patterns are similar for men and women. Although we estimate (1) for all years in our data, we define good jobs based on industry fixed effects estimated for the year 2000, which is the midpoint in our study period, such that any change in CZ employment in good jobs is due to changes in employment across a fixed set of industries and not to changes in which industries are designated as high wage.

We define as good jobs those in industries in the top one-third of estimated industry fixed effects, $\alpha_{i(j)}$, where we form terciles by weighting industries by national employment of full-time, prime-age workers.[13] For most of our analysis, we define industries using the 206 Census IND1990 industry codes,[14] which allows us to have a common set of industry identifiers for the entire 1980 to 2021 period. Consistent with earlier evidence (Groshen, 1991), the industry fixed effects we estimate for the year 2000 are very similar to those for other years.[15] In Figure A4, we project CZ shares of national employment in good job industries in 2000, based on industry fixed effects estimated for 2000, on CZ good job industry employment shares in 2000, based on industry fixed effects estimated for 1980, which yields a slope coefficient of 1.05 and an R^2 of 0.99 (weighted by the CZ working-age population in 2000). The corresponding correlations are similarly high when we examine industry effects estimated for college and non-college workers separately, as seen in Figure A5.

We also estimate industry fixed effects for the 252 Census NAICS industry codes,[16] which are available for 2000 forward and which are similar to the industry identifiers used by Card et al. (2024), whose results we discuss in detail below. Whether we examine CZ shares of national employment in good jobs or the ranking of these shares across CZs, we find very similar patterns when using the more-aggregate IND1990 codes as when we use the less-aggregate NAICS codes (see Figure A6).[17]

It is worth noting that the CZs that account for most employment in good jobs industries are themselves large, as seen in Table A2. The second and third rows of the table show the share of the US population in CZs that in the relevant year are in the top tercile or top decile of the distribution of the national share of good jobs, respectively; the fifth and sixth rows of the table show corresponding entries for shares of total US employment. CZs in the top third

[13] Using industry fixed effects for 2000 and the top-tercile designation of good job industries for that year, Figure A2 shows that the share of employment in good job industries fell from 36.4% in 1980 to 30.4% in 2021. In Figure A3, we see that the decline in employment in good job industries was largest among workers without a BA degree (and especially large for native-born, non-Hispanic, non-college whites). The only group of workers to experience large increases in the share of employment in good job industries over the 1980 to 2021 period were foreign-born workers with a BA degree.

[14] We standardize these codes using the crosswalk in Dorn (2009), modified to create a time-consistent set of IND1990 industry codes from 1980 to 2021. Of the 206 IND1990 industries, 65 are designated as good jobs industries for the sample of all workers in 2000, 77 for the sample of workers with a college degree in 2000, and 57 for the sample of workers without a college degree in 2000 (where the varying numbers of industries reflect differences in industry size, given we use industry employment to weight the distribution).

[15] A regression of the industry effects based on 2000 data on the industry effects based on 1980 data yields a slope coefficient of 1.000 (0.001) and a R^2=0.999, indicating the estimates are virtually indistinguishable.

[16] We use the Ipums.org NAICS industry code crosswalk, modified to create a time-consistent set of full-digit NAICS industry codes from 2000 to 2021.

[17] For both 2000 and 2021 (shown in the first row of Figure A6), the R^2 from the regression of log CZ shares of national employment of good jobs based on IND1990 industries on that for NAICS industries is 0.999. The correlation is similarly tight when we consider good job employment shares in 2000 for college and non-college workers separately (as seen in the second row of the figure).

of the good jobs distribution account for 80 to 82 percent of US population and employment, while CZs in the top tenth account for 55 to 59 of US population and employment.

Relatedly, we also note that in the cross-sectiononal elasticity of the number of good jobs with respect to CZ size is above 1 indicating that large CZs have more good jobs per capita than small CZs. For example, when we regress the log of number of goods jobs on the log of CZ adult population for the year 2000, we find a coefficient of 1.059 (0.007), which means that in 2000 large CZ accounts for a disproportionate share of employment in good job industries. A similar pattern emerges in 2021.

2.3 Selection Bias from Worker Sorting across Industries

Our estimates of industry wage premia in equation (1)—and therefore our identification of which jobs are good jobs—come from cross-sectional data. Industry premia are identified by comparing workers across industries, holding constant their observable characteristics. An important concern is that our estimates of industry wage premia may be confounded by worker sorting across industries. If, conditional on the controls included in (1), workers with the strongest unobservables (i.e., with the highest unmeasured earnings potential) tend to select into a subset of industries, our estimates of the $\alpha_{i(j)}$ terms in equation (1) would be biased: they would reflect not just industry wage premia but also unobserved worker ability (Krueger and Summers, 1988; Murphy and Topel, 1990). This bias, if large enough, could lead us to misclassify which industries offer good jobs. This would be the case, for instance, if one or more industries entered the top tercile of the conditional wage distribution solely because of the high unobserved quality of its workforce.

Concerns about worker selection are well-founded. Higher wage workers, defined as those with larger estimated worker fixed effects in wage regressions using longitudinal data, tend to select into larger cities in which their earnings prospects tend to be larger (Glaeser and Maré, 2001; Combes et al., 2008). Higher wages for more productive workers in these locations may arise from enhanced prospects for learning on the job (Roca and Puga, 2017) or improved opportunities for matching with employers (Dauth et al., 2022; Amior, 2024).[18] For their part, more productive firms also tend to select into larger cities (Gaubert, 2018), where they are more likely to hire high-wage employees (Abowd et al., 1999).

The endogenous spatial sorting of workers and firms does not necessarily negate the validity of industry fixed effects estimated using cross-sectional data. Because high-wage workers select into the high-productivity firms that comprise high-premium industries, estimates of the *magnitude* of industry wage premia derived from cross-section data may be

[18]More productive workers may also be drawn to larger cities because of the amenities created by their geographic concentration in those locations (Diamond, 2016).

biased, as Card et al. (2024) find to be the case. But this does not necessarily mean that the *ranking* of industries in terms by their wage premia will be biased, too. If, for instance, there is assortative matching of workers to industries, based on the earnings potential of the former and the productivity of the latter, the ranking of industries by wage premia in the cross-section (i.e., average industry earnings, conditional on worker observables) may be very similar to that based on wages in longitudinal data (i.e., conditional on time-invariant worker characteristics). It is thus an empirical question whether the industry fixed effects we estimate in (1) are useful for categorizing high-wage industries.

To evaluate potential bias, we compare our results to Card et al. (2024), hereafter CRY, who estimate industry fixed effects by applying an AKM model (Abowd et al., 1999) to longitudinal data on worker earnings from the LEHD for the period 2008 to 2019. The longitudinal nature of the data allows them to estimate industry premia conditioning on worker and CZ fixed effects. Their estimates of industry fixed effects are thus identified by comparing the same worker over time in different industries. As such, their estimates account for time-invariant worker heterogeneity.[19] If there are significant differences in unobserved worker earnings potential across industries that affect the ranking of industries in terms of earnings premia, our definition of good jobs based on cross-sectional estimates of industry premia would be likely to differ significantly from theirs. On the other hand, if either worker selection is limited (such that differences in unobserved worker earnings potential across industries are small) or selection does not upset the ranking of industries in terms of estimated earnings premia, the two sets of estimates would be similar.

As a first exercise, we compare the magnitude of our estimated industry wage premia in 2000 with estimates in CRY based on 2008 to 2019.[20] Since the CRY industry classification uses NAICS industry codes, to compare our estimates with theirs we first harmonize our respective industry identifiers.[21] When comparing the industry premia from our 2000 sample to CRY, we find a correlation of 0.83 at the 4-digit industry level (206 industries), 0.84 at the 3-digit industry level (89 industries), and 0.86 at the 2-digit level (24 industries), as seen in Table A3 and Figure A7 (where industries are weighted by national employment). Our

[19]The AKM approach used by Card et al. (2024) requires that industry, place, and worker fixed effects are separable. That is, the impact on earnings of moving from one industry (or region) to another is common across workers. They find weak evidence of interaction effects between industry and place, consistent with AKM assumptions. They find further that industry wage effects are symmetric for industry leavers and industry joiners, consistent with the absence of systematic differences between the two groups of workers.

[20]We cannot compare their estimates to ours for years before 2000, since the LEHD is only available for recent decades.

[21]To do so, we take NAICS 4-digit code industry fixed effects in Appendix Table A-2 of CRY and assign them to Census/ACS NAICS codes using a crosswalk that merges on 4-digit, 3-digit, and 2-digit codes (we use more aggregate industries when we cannot match on disaggregate codes). We are able to link 206 of the 221 industries in our data; for comparison, CRY have 311 4-digit NAICS codes in their analysis.

estimates are thus highly correlated with theirs in terms of magnitude. Turning to industry rankings of estimated fixed effects, we find similarly high correlations of 0.84, 0.87, and 0.83 at the 4-digit, 3-digit and 2 digit-industry levels, respectively.

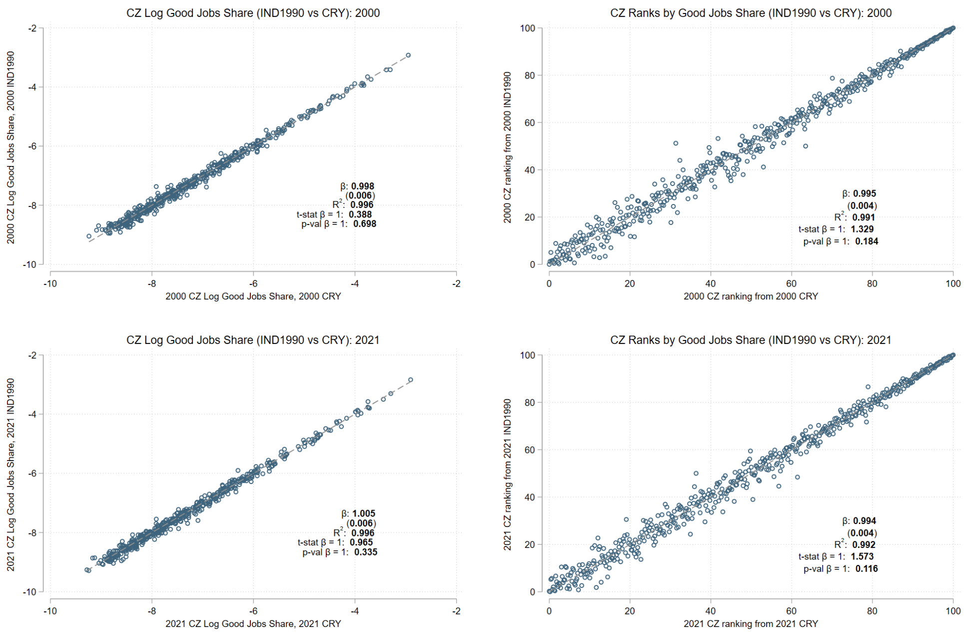
As a second exercise, we turn to the even more important comparison (for our purposes) of CZ employment in good jobs based on our estimates versus those in CRY. We define the share of CZ c in national employment in good jobs in year t as

$$Share^g_{ct} = \ln\left(\frac{Emp^g_{ct}}{\sum_{c'} Emp^g_{c't}}\right) \tag{2}$$

where Emp^g_{ct} is employment in good job industries in CZ c and year t. This comparison helps us determine whether our main empirical objects of interest are spatially biased due to unobserved worker quality. Even if they are not spatially biased, the comparison is useful because it provides a reliability ratio, and therefore helps us quantify how much measurement error they contain. To perform the comparison, we use the CRY designation of good job industries (i.e., industries in the top tercile of their estimated industry fixed effects for 2008 to 2019 in LEHD data) to calculate (2) using Census/ACS data for 2000 and 2021. We thus import their industry rankings into our Census/ACS data on CZ industry employment. We then use our estimated industry fixed effects (based on IND1990 industries in 2000 in Census data) to estimate (2) for the same years.[22]

[22]Note that our estimated industry fixed effects differ from theirs in four respects: data source (we use the Census 5% sample, whereas CRY use the LEHD), time period (we use our mid-point year of 2000, whereas CRY use 2008 to 2019), estimation method (we use cross-section regressions, whereas CRY use an AKM estimator), and industry classification (we use IND1990 industries, whereas CRY use NAICS industries). As we show in the previous section, we obtain identical results in our data using IND1990s or NAICS industries. We use the former so that we can extend our analysis back to 1980.

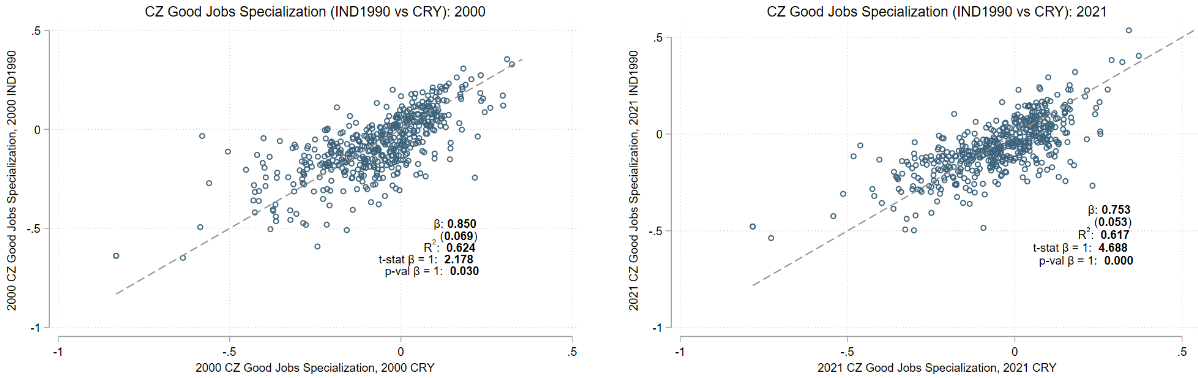
Figure 1: CZ Shares of Good Jobs: IND1990 vs. CRY Industries



Notes: Each graph plots CZ log good job shares (or rankings of good job shares) based on our estimated industry fixed effects for 2000 on the y-axis against CZ log good job shares (or rankings of good job shares) based on CRY estimated industry fixed effects on the x-axis. Results for 2000 appear in the first row and for 2021 in the second row; results for CZ log good job shares appear in the left panels and for CZ rankings of good job shares in the right panels. The reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in 2000.

In Figure 1, we plot our estimates of (2) on the vertical axis against CRY-based estimates on the horizontal axis. The first row of the figure shows results for CZ industry employment in 2000, while the second row shows results for 2021; the left panels plot log CZ employment shares, while the right panels plot the rankings across CZs of these values. In either year and using either CZ employment shares or rankings of these shares, the slopes are between 0.994 and 1.005 (and not statistically different from 1) and the R^2 values range from 0.992 to 0.996. Overall, this suggests that our estimates are nearly identical to those based on CRY. Given the definition of good job share, this high degree of correlation should be interpreted as reflecting both the number of good jobs in a CZ and CZ size.

Figure 2: CZ Specialization in Good Jobs: IND1990 vs. CRY Industries



Notes: The graphs plot CZ log good job specialization based on our estimated industry fixed effects for 2000 on the y-axis against CZ log good job specialization based on CRY estimated industry fixed effects on the x-axis. Results for 2000 appear in the left panel and for 2021 in the right panel. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in 2000.

To anticipate our later empirical analysis, we also examine CZ specialization in good jobs, defined as the share of CZ c in national employment in good jobs industries relative to the share of CZ c in national employment in all industries:

$$Specialization_{ct}^{g} = \ln\left(\frac{Emp_{c,t}^{g}}{\sum_{c'} Emp_{c,t}^{g}}\right) - \ln\left(\frac{Emp_{c,t}}{\sum_{c'} Emp_{c',t}}\right) \tag{3}$$

where Emp_{ct} is total employment in CZ c in year t. Figure 2 replicates the structure of Figure 1 now using the value in (3) in place of that in (2). In 2000, the slope is 0.85 and the R^2 is 0.62; while in 2021, the slope is 0.75 and the R^2 is 0.61. Because the quantity in (3) involves a difference between local and national industry employment shares—i.e., we are evaluating the deviation in the CZ good jobs share from the CZ total employment share—there may be a loss of systematic variation in the data when compared to (2), which may account for the weakening of the correlation with the CRY-based measure. Nevertheless, although the correlation is less tight than in Figure 1, quantitatively our metric retains a high degree of correlation with that based on estimates in CRY.

From the comparison of our results with CRY, we conclude that our definition of good jobs does not appear to be overly contaminated by unobserved worker quality caused by systematic worker selection across industries. We caution, however, that we cannot replicate this test for 1980; the degree of worker sorting in the earlier sample is unknown.

3 Good Job Industries and Regions

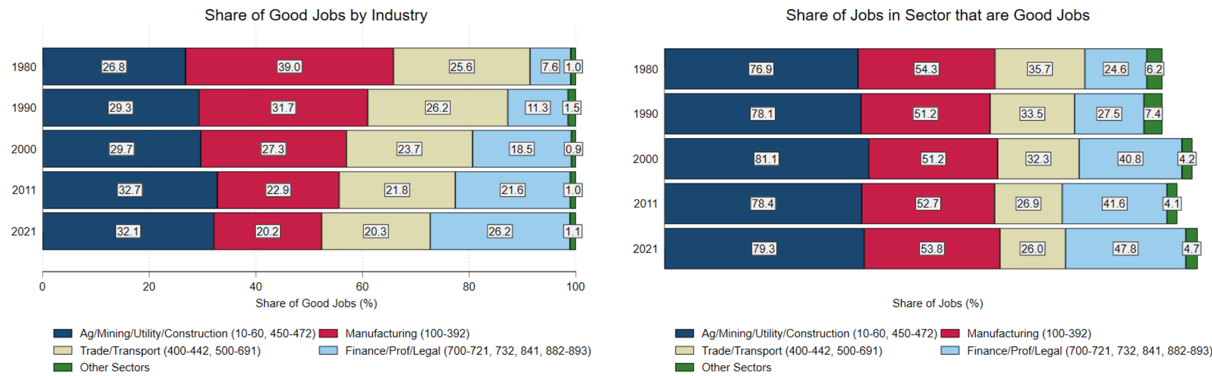
As a prelude to our analysis of the changing spatial distribution of good job industries in Section 4, we discuss the industries that are the sources of good jobs, the regions that host most good jobs, and broad patterns of how each have changed over time. The descriptive evidence reveals the scale of the reallocation of good jobs out of manufacturing, the changing composition of good jobs within sectors, and how the regional manifestations of these movements differed before and after 2000 and according to worker educational attainment.

3.1 Good Job Industries

To illustrate how the industry composition of employment in good jobs has evolved over time, we start by aggregating industries into five broad sectors: (a) agriculture, construction, mining, and utilities; (b) manufacturing; (c) trade and transport; (d) business and professional services (finance, insurance, real estate, legal services, professional services, and information technology); and (e) other sectors.[23] Figure 3 displays shares of each sector in national employment in good jobs (left panel), and shares of employment in each sector comprised by goods jobs (right panel), over the 1980 to 2021 period. We see evidence of two of the most important structural shifts in US industry composition over the last four decades: the decline of manufacturing employment and the rise of human capital-intensive service industries. The share of good jobs held by workers employed in manufacturing plunged from 39.0% in 1980 to 20.2% in 2021, coinciding with the drop in overall US manufacturing employment during the period. Concomitantly, the share of good jobs in business and professional services nearly quadrupled, from 7.6% in 1980 to 26.2% in 2021, indicating that human capital-intensive services are an increasingly important source of good jobs for US workers. There were less dramatic changes over the period in the share of good jobs in employment in agriculture, construction, mining, and utilities, which increased modestly, and in trade and transportation, which declined modestly.

[23]The health, education, and public administration sectors do not appear in the figure, as none has any industries in the top tercile of estimated industry fixed effects.

Figure 3: Good Job Employment by Sector, 1980 to 2021



Notes: These figures show the distribution of full-time, prime-age employment across major sectors for our definition of good job industries (industries in the top tercile of industry wage fixed effects for 2000). The left panel shows shares of national employment in good job industries account for by each sector; the right panel shows the share of employment within each sector that is in good job industries. Sectors are based on IND1990 codes: Agriculture, Mining, Utilities, and Construction (10-60, 450-472); Manufacturing (100-392); Trade and Transportation (400-442, 500-691); Finance, Professional, Legal, and IT Services (700-721, 732, 841, 882-893); Health and Education Services (812-840, 842-881); Other Services (722-731); and Public Administration (900-932). (Note that Health, Education, and Public Administration are excluded as they have no top tercile industries.)

To give a better sense of which industries account for most good jobs, Table 1 lists the five largest industries for good jobs within each broad sector. In the first sector, construction is by far the largest source of good jobs, with its share of the sectoral total rising from 71.0% in 1980 to 82.5% in 2021.[24] Within manufacturing, good jobs are spread relatively evenly across industries. The largest sources of good jobs—motor vehicles, electrical machinery and household electronics, machinery and computing equipment, aircraft, and pharmaceuticals—saw their collective share of the manufacturing total rise from 52.5% in 2000 to 57.8% in 2021, with motor vehicles displacing electrical machinery in the top spot. he share of manufacturing good jobs in electrical machinery and household electronics peaked at 17.2% in 2000 (see Table 1), just prior to the dot-com bust and the acceleration of the China trade shock, both of which appear to have contributed to job loss in the industry.

[24]In Table A4, which shows the five largest occupations for employment in good jobs in each of the five sectors, we see that the largest good job occupations in agriculture, construction, mining, and utilties are construction laborers, at 14.6% in 2021, and managers and administrators, at 13.5% in 2021.

Table 1: Industry Shares of Good Jobs by Sector

Industry	Employment Share 1980	2000	2021
Agriculture/Mining/Utility/Construction			
All construction (60)	71.0	82.1	82.5
Electric light and power (450)	8.4	6.7	5.3
Sanitary services (471)	3.0	4.0	4.6
Oil and gas extraction (42)	6.0	2.6	3.9
Gas and steam supply systems (451)	2.2	1.7	1.4
Manufacturing			
Motor vehicles and motor vehicle equipment (351)	11.6	15.7	17.4
Electrical machinery, equipment, and supplies, n.e.c. (342)	11.6	17.2	12.7
Machinery, except electrical, n.e.c. (331)	9.5	10.7	11.7
Aircraft and parts (352)	5.6	4.7	8.4
Drugs (181)	2.0	4.2	7.6
Trade/Transport			
Trucking service (410)	19.6	25.4	34.8
Motor vehicle dealers (612)	11.0	12.5	13.9
Telephone communications (441)	18.9	17.1	13.5
Radio and television broadcasting and cable (440)	2.8	7.2	9.0
U.S. Postal Service (412)	10.4	11.6	7.6
Finance/Professional/Legal Services			
Computer and data processing services (732)	18.5	26.5	37.7
Management and public relations services (892)	15.7	14.8	16.4
Engineering, architectural, and surveying services (882)	26.8	18.7	14.8
Security, commodity brokerage, and investment companies (710)	15.5	18.5	14.6
Credit agencies, n.e.c. (702)	13.9	13.3	10.7

Notes: This table presents the distribution of employment of full-time, prime-age workers across good job industries within five major industry sectors. Within each sector, we list the five largest industries for good job employment in 2021. See Figure 3 for sector definitions.

Within trade and transport, the share of good jobs in trucking, the top industry for good jobs in all years, rose from 19.6% in 1980 to 34.8% in 2021, while the share in telephone communications fell from 18.9% in 2000 to 13.5% in 2021 (from rank two to rank three in the sector), during a period in which industry deregulation and the advent of cellular communications upended how telephone services are provided.[25] There is similar churning

[25]Truck driving is the top occupation for good jobs in the trade and transport sector, at 20.7% of the total

in good jobs across industries within business and professional services. The share of good jobs in computer and data processing nearly doubled from 18.5% in 1980 to 37.7% in 2021, moving it into the top spot in the sector, while the good jobs share in architecture and engineering services (which does not include IT industries) dropped from 26.8% in 1980 (rank one) to 14.8% in 2021 (rank three).[26]

When we examine the allocation of good jobs across industries separately for workers with and without a BA, as shown in Figure A8, we see that the decline in the share of good jobs in manufacturing was comparable for college workers (from 38.9% in 1980 to 20.3% in 2021) and non-college workers (from 39.0% in 1980 to 20.2% in 2021). There is no such similarity between the two groups in the sectors in which good job employment shares rose. For college workers, the increase in good job shares occurred entirely in business and professional services (from 20.0% in 1980 to 49.0% in 2021), while for non-college workers it occurred almost entirely in agriculture, construction, mining, and utilities (from 28.5% in 1980 to 43.5% in 2021), with construction being by far the largest contributor. For college workers good jobs have reallocated from one highly tradable industry—manufacturing—to a largely tradable one—business and professional services—whereas for non-college workers good jobs have reallocated primarily to non-tradable construction.

The literature has studied these sectoral shifts. Charles et al. (2016) find that job growth in construction during the early 2000s housing boom temporarily masked job loss in manufacturing for less-educated workers, while Autor and Dorn (2013) and Deming (2017) document that after 1980 jobs in middle-wage occupations intensive in repetitive tasks, including manufacturing, were reallocated to low-wage occupations intensive in manual tasks (for non-college workers) and to high-wage occupations intensive in cognitive tasks and social skills (for college workers). The literature has paid less attention to variation in changes in the tradability of high-wage work according to educational attainment. The apparent increase in the concentration of good jobs for non-college workers in non-traded activities may indicate that their opportunities for high-wage employment in a local labor market have become more dependent on growth in tradable activities that primarily employ the college educated. The spatial demand for non-college workers in good job industries may therefore increasingly derive from the labor intensity of the non-traded goods that college workers demand, an impression for which we find empirical support in Section 4.2.

The right panel of Figure 3 captures changes in the composition of jobs within sectors. Notably, the share of manufacturing employment in good job industries was stable over

in 2021, up from 14.5% in 1980, as seen in Table A4.

[26]In 2021, the top occupations for good jobs in the sector were managers and administrators at 13.3% (up from 11.1% in 1980), computer programmers at 12.3% (up from 3.1% in 1980), and computer system analysts and computer scientists at 11.0% (up from 2.6% in 1980), as seen in Table A4.

time—at approximately 54 percent in both 1980 and 2021—indicating that the decline in the manufacturing share in the left panel was fully attributable to the relative decline in total manufacturing employment and not to a decline in the relative earnings of manufacturing workers. Despite the precipitous drop in labor demand and employment in the sector, the majority of manufacturing jobs still appear to pay well. These patterns hold for both college and non-college workers in manufacturing (Figure A8). Whereas the good job share in manufacturing was largely unchanged, it nearly doubled in business and professional services, rising from 24.6% in 1980 to 47.8% in 2021. Predictably, the growth of the share of employment in good job industries in business and professional services was larger for workers with a BA (from 29.3% in 1980 to 53.2% in 2021) but was still sizable for workers without a BA (from 21.6% in 1980 to 37.6% in 2021), as shown in Figure A8.

Taken together, the left and right panels of Figure 3 indicate that human capital-intensive service industries not only experienced a large increase in their relative size but also a significant increase in the fraction of their workers that are employed in high wage industries and can therefore be classified as holding a good job. The good job share of employment in agriculture, construction, mining, and utilities was stable over the four decades, while the good job share in trade and transportation declined from 35.7% to 26.0%, due in part to the expansion of jobs in the low-wage retail sector.[27]

3.2 Good Job Regions

To prepare for our analysis of the dynamics of regional employment in good jobs in Section 4, we visualize changes in the location of good jobs over time. For the time periods 1980 to 2000 and 2000 to 2021, we map changes in the log CZ share of good jobs (i.e., the CZ share of national employment in good job industries as defined in equation (2)), and the log CZ specialization in good jobs (i.e., the CZ share of national employment in good job industries relative to the CZ share of national employment in all industries as defined in equation (3)). Changes in CZ shares of employment in good job industries indicate absolute movements of good jobs across local labor markets, while changes in CZ specialization in good job industries indicate whether CZs have increased or decreased the fraction of their workers who hold good jobs, holding constant CZ total employment.

In interpreting the patterns we uncover, it is important to keep in mind that the total employment of a commuting zone is endogenous to the presence of good jobs. Consider a CZ that for some exogenous reason attracts a firm that creates 100 new good jobs. The

[27]Figure A8 shows that the decline in the share of trade and transport employment in good job industries was roughly twice as large for non-college workers (35.8% in 1980 to 24.6% in 2021) than for college workers (35.1% in 1980 to 20.6% in 2021). On the labor market impacts of the rise of big-box retailers, such as Walmart and Target, see Coviello et al. (2022), Dube et al. (2022), and Naidu and Sojourner (2020).

CZ will likely experience an increase in total employment of greater than 100 jobs, due to a likely increase in employment in non-tradable services caused by expanded local consumer or industrial demand (Moretti, 2010). Despite the fact that the absolute number of good jobs has unambiguously increased, the specialization metrics for this CZ may increase or decrease, depending on the number and salaries of new jobs created in the non-tradable sector. While describing changing specialization patterns, we discuss quantitative spatial frameworks which may be able to account for them.

Motivated by findings in Section 3.1 on changes in sectoral specialization by worker education, we examine these patterns separately for workers with and without a BA degree. There is a large body of evidence that technological change (Katz and Autor, 1999) and globalization (Autor et al., 2016) have differentially affected workers without a college degree. Because industries exposed to these shocks tend to be geographically concentrated (Autor et al., 2015), changes in the location of good jobs for college workers may have diverged from that for non-college workers. Relatedly, because more-educated workers tend to be more mobile geographically (Amior, 2024) and because the benefits of locating in larger cities appear to be greater for the college educated (Diamond, 2016; Diamond and Gaubert, 2022), those with less education may have missed out on some opportunities.[28]

The powerful secular shifts apparent in Figure 3, in which good jobs have reallocated from less-education-intensive manufacturing to more-education-intensive business and professional services, may raise the concern that any geographic patterns we uncover would be simply a spatial restatement of the well-known fact that since 1980 there has been a strong increase in the relative demand for more-educated labor (Katz and Autor, 1999). Forestalling such concerns is in part why we estimate two sets of industry fixed effects: one for the full sample of workers (in which industry fixed effects are conditioned on worker educational attainment), and one for subsamples of workers with and without a BA degree (in which we implicitly allow for interactions between industry wage premia and college attainment). In our analysis of the dynamics of CZ good job shares and good job specialization, we use both sets of fixed effects. The maps in Figures 4 and 5 use the second set of industry fixed effects (estimated separately for college and non-college workers), and therefore highlight changes in the location of employment in good job industries within skill groups.

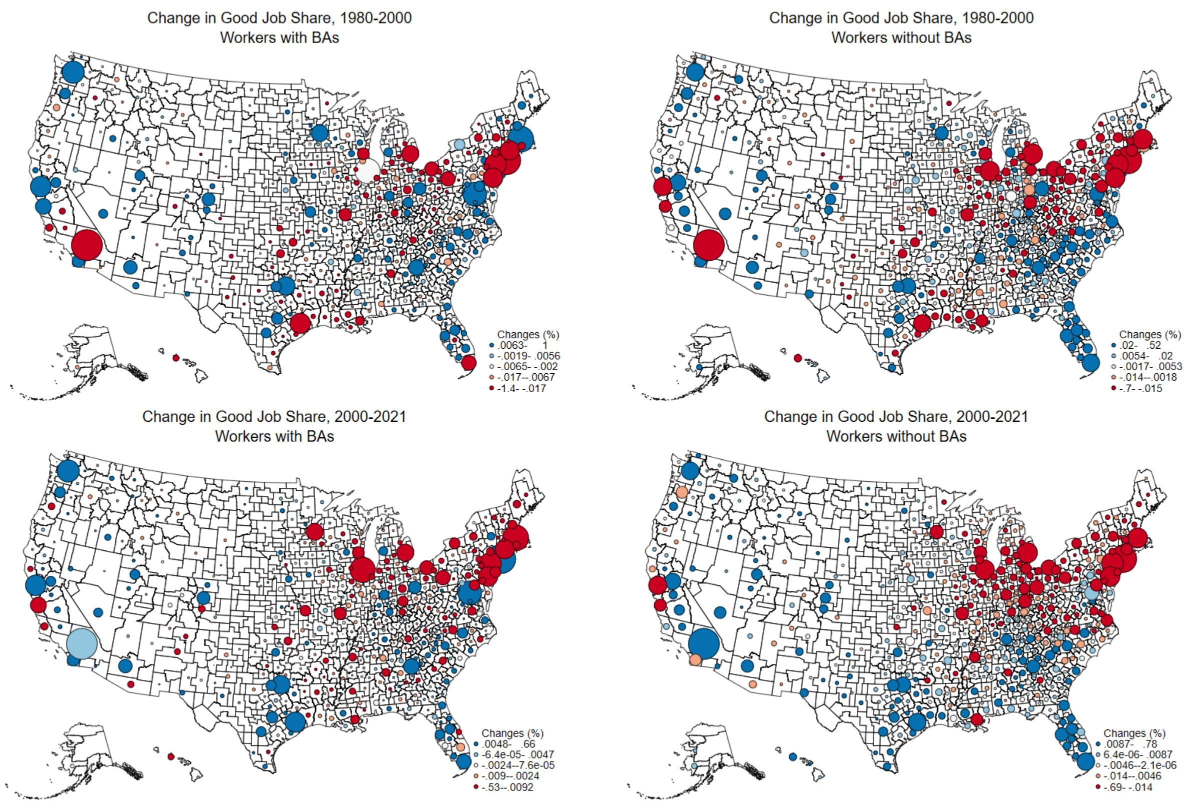
3.2.1 Concentration of Good Job Industries

The top left panel of Figure 4 maps the change in the good job share in equation (2) for college workers over 1980 to 2000, while the top right panel maps the corresponding change for non-college workers. The bottom two panels repeat the exercises for the 2000 to 2021

[28]The migration responses of very-high-income individuals appear to be highly elastic to changes in local economic conditions (Kleven et al., 2020; Moretti and Wilson, 2023).

period. Blue circles indicate CZs in the top two quintiles of changes (above the median), red circles indicate CZs in the bottom two quintiles of changes (below the median), and white circles indicate CZs in the middle quintile of changes (around the median). The radii of the circles indicates the size of CZ populations in the initial period (1980 or 2000).[29]

Figure 4: Changes in CZ Good Job Shares, 1980-2000 and 2000-2021



Notes: These figures map changes in CZ log good job shares (share of national employment in good job industries) over 1980-2000 (first row) and 2000-2021 (second row). Left panels apply to workers with a BA degree; right panels apply to workers without a BA degree. Dot sizes indicate CZ population size at the start of each period. Blue shading indicates changes in the top two quintiles, white shading indicates changes in the middle quintile, and red shading indicates changes in the bottom two quintiles (for each time period).

For college workers (left panels of Figure 4), there is a checkerboard pattern to changes in CZ shares of national employment in good job industries, such that within each region some CZs have above median changes (positive, blueish dots) and other CZs have below median changes (negative, redish dots). Further, some CZs switch from above median growth to below median growth, or vice-versa, from one two-decade period to the next. In the

[29]The employment weighted sum of the changes across CZs is zero by construction, though the number of CZs with positive changes in shares depends on whether good job growth was concentrated in larger CZs (meaning fewer CZs with blue dots) or smaller CZs (meaning more CZs with blue dots).

Northeast, for instance, over 1980 to 2000 Boston and Washington, DC, have positive (above median) growth but New York City, Newark, and Philadelphia have negative (below median) growth. After 2000, New York switches to positive growth in good job shares, while Boston switches to negative growth. Similarly, on the West Coast Los Angeles switches from falling good job shares before 2000 (during a regional contraction in manufacturing employment following the end of the Cold War) to rising shares after that date, while San Jose exhibits the opposite pattern (strong growth before the 2000 dot-com bust and weak growth afterward). Although each region comprises a mix of CZs with expanding and contracting shares of national employment in good jobs, the preponderance of shares fell in the Midwestern CZs that span the Rust Belt (especially after 2000) and rose in CZs in the South and Mountain West (also, especially after 2000). For the college educated, economic opportunity appears to have moved to southern and western states.[30] Within each region, there is no discernible correlation between good job growth and CZ size, a finding we reexamine in Section 4.

For non-college workers (right panels of Figure 4), there is strong variation across regions in changes in good job shares. Good job shares fell in CZs across the Northeast and northern Midwest, while they rose across much of the South and Mountain West. These patterns appear to intensify after 2000. Indeed, over the 2000 to 2021 period, good job shares fell nearly uniformly in Illinois, Massachusetts, Michigan, Ohio, New York, Pennsylvania, and West Virginia, and rose nearly uniformly in Florida, Nevada, New Mexico, Oklahoma, Texas, and Utah. These regional patterns aside, for non-college workers there again appears to be little discernible corelation between CZ size and good job growth in either period.

To see what the regional reallocation of good jobs in Figure 4 implies about changes in regional industry composition, Figure A9 plots changes in the shares of jobs in a region that are in manufacturing good job industries (in red) and non-manufacturing good job industries (in blue), following a plot ordering similar to Figure 4. Over 1980 to 2000, for college workers in all regions the share of employment in non-manufacturing good jobs rose and the share of employment in manufacturing good jobs fell. Because the former changes dwarfed the latter everywhere, the share of employment in good jobs for college workers rose overall. After 2000, although sign patterns for sectoral and regional changes in good job shares remained the same, falling employment shares in manufacturing good job industries well exceeded rising employment shares in non-manufacturing good job industries, such that the regional share of employment in good jobs fell across the board.[31]

[30] CZs with rising good job shares in both time periods include Atlanta, Charlotte, Dallas-Forth Worth, Denver, Phoenix, Portland, San Francisco-Oakland, and Seattle.

[31] A further difference for college workers between the two periods is that whereas before 2000 the loss of manufacturing good jobs was largest in the Midwest and Northeast, after 2000 it was largest in the West (during a period in which technology industry clusters, which predominate in the West, were shifting from

For non-college workers, the changes are starker. In the Midwest and Northest, the falling share of employment in manufacturing good jobs exceeded the rising share of employment in non-manufacturing good jobs in both time periods; in the South and West, rising employment shares in non-manufacturing good jobs more than offset falling employment shares in manufacturing good jobs over 1980 to 2000 but not over 2000 to 2021.

We are left with a picture in which there was a loss of good jobs in manufacturing for college and non-college workers in all regions and in both time periods. Although the manufacturing drag on good jobs was stronger in the Rust Belt and weaker in the Sun Belt, it was manifest everywhere. And while the decline in manufacturing good jobs was larger before 2000, its net impact on overall in employment shares in good jobs was larger after 2000, owing to a sharp slowdown in the growth of employment in non-manufacturing good job industries. After 2000, growth of good job service industries—primarily business and professional services for college workers and construction for non-college workers—could not keep pace with the continued decline of manufacturing.

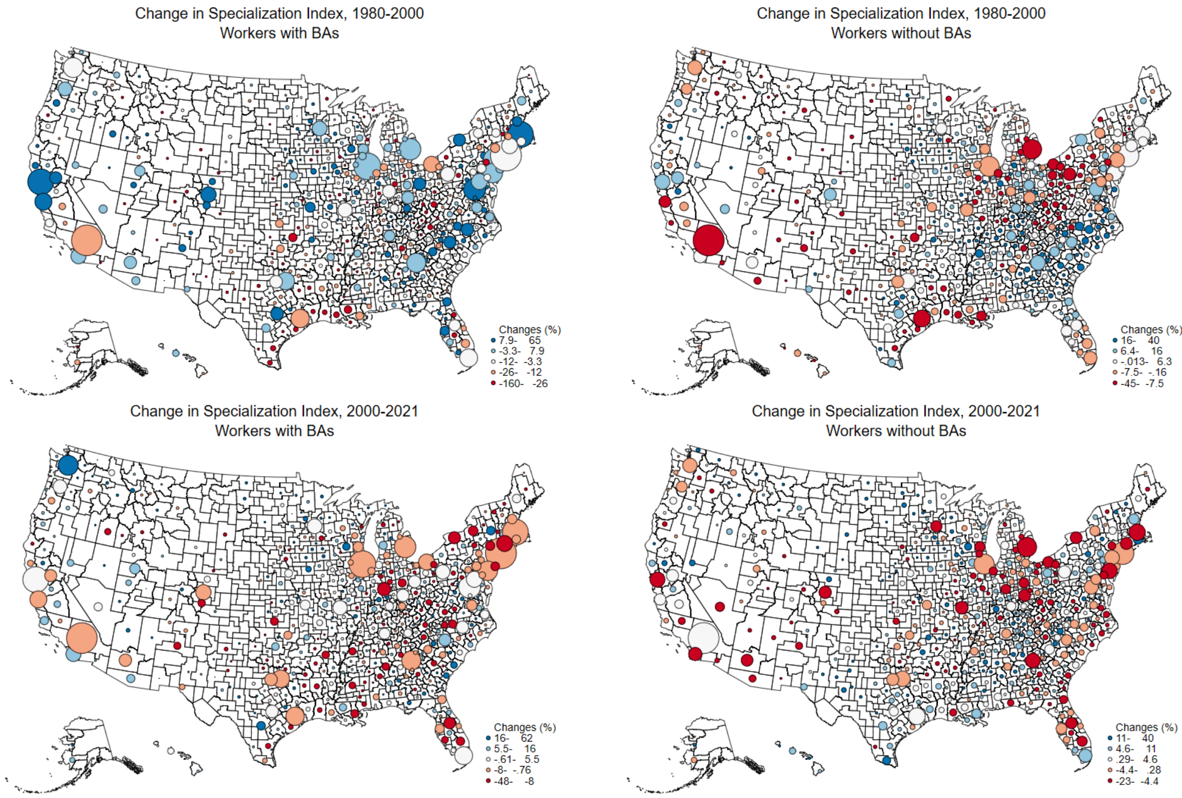
3.2.2 Specialization in Good Job Industries

Because changes in CZ good job shares shown in Figure 4 do not control for changes in CZ size, the observed patterns may in part reflect overall reallocations of employment across commuting zones. To evaluate changes in CZ specialization in good jobs, in which we do adjust for changes in CZ size, Figure 5 maps changes in the value in equation (3). Whereas the (weighted) average of changes in CZ good job shares must equal zero, there is no such restriction in changes in CZ specialization in good jobs. In any given time period, CZ specialization in good jobs may rise or fall across the board, depending on whether national employment shares in good job industries are rising or falling.

In the upper left plot of Figure 5, we see that for college workers over 1980 2000, increasing specialization in good jobs appeared to be stronger in larger CZs. Most of the larger circles (indicating larger CZ populations in 1980) appear to be light or dark blue (indicating above median changes), while the many smaller circles (indicating smaller CZ populations) appear to be white or red (indicating below median changes). For non-college workers over 1980 to 2000, shown in the upper right plot, there appears to be wider regional variation in changes in good job specialization. Specialization rose by more in larger CZs in the Southeast (except in Florida), rose by less in larger CZs in the northern Midwest, and exhibited a mixed pattern of changes in the Great Plains, Mountain West, and West Coast.

the manufacture of electronics hardware to the production of software and digital services).

Figure 5: Changes in CZ Specialization in Good Jobs, 1980-2000 and 2000-2021



Notes: These figures map changes in CZ log good job specialization (share of national employment in good job industries/share of national employment in all industries) over 1980-2000 (first row) and 2000-2021 (second row). Left panels apply to workers with a BA degree; right panels apply to workers without a BA degree. Dot sizes indicate CZ population size at the start of each period. Blue shading indicates changes in the top two quintiles, white shading indicates changes in the middle quintile, and red shading indicates changes in the bottom two quintiles (for each time period).

For the 2000 to 2021 period, shown in the bottom two panels of Figure 5, changes in good job specialization are quite different from the earlier period. For non-college workers, shown in the lower right plot, the preponderance of larger CZs appear to be in the bottom two quintiles of changes in good job specialization (as indicated by the many larger circles that are light or dark red). For college workers over 2000 to 2021, shown in the lower left plot, changes in specialization patterns are qualitatively similar—most larger CZs appear to have had below median changes in good job specialization—though quantitatively smaller—larger CZs tend to be in the fourth rather than the fifth quintile (i.e., for college workers there are more light red circles, while for non-college workers there are more dark red circles).

Summary. Since 1980, all regions have seen a fall in the share of employment comprised by good job industries in manufacturing. Even Southern states have not escaped the decline, despite the increased attractiveness of the region to manufacturing employers (Erickcek et al., 2012). The South, which was relatively exposed to the adverse impacts of globalization (Autor et al., 2016; Choi et al., 2024), lost good jobs in manufacturing just like everywhere else, though not of the same magnitude as in the rapidly deindustrializing Midwest and Northeast. The demise of good jobs in manufacturing hit non-college workers especially hard, as relatively few good jobs were created outside the sector for workers without a BA degree. Whereas new service jobs for college graduates tended to be in industries that offer high earnings—such as accounting, finance, IT, management, and legal services—new service jobs for workers without college tend to be in industries that offer low earnings—including hotels and restaurants, personal services, and the low-wage end of health care. Construction was the one bright spot for growth in good jobs for non-college workers.

These patterns, though quantitatively stronger in some regions than in others, were present throughout the US. Perhaps because the swapping of good jobs in manufacturing for good jobs in other sectors was stronger over 1980 to 2000 than over 2000 to 2021, there appeared to be a decrease in regional specialization in good jobs after 2000. Although superstar cities are where the college educated gather to find high-paying jobs in consulting, finance, high tech, and related activities (Florida, 2003; Moretti, 2012), and to enjoy the enhanced amenities that arises from their geographic concentration (Glaeser et al., 2001; Diamond, 2016), larger metropolitan of late areas appear to have seen reduced relative employment in good jobs, both for workers with and without a BA degree.

The patterns we find have an obvious connection to the large labor economics literature that documents the sharp increase in income and wage inequality, which began in the early 1980s and which has been reflected in an increase in the college earnings premium caused by the rising demand for worker skill (Katz and Murphy, 1992; Krueger, 1999; Lemieux, 2006; Autor et al., 2008; Autor and Dorn, 2013). The profound sectoral shifts in the source of good jobs in this period were likely important factors in raising the demand for workers with a college education relative to the demand for workers without a college education. Yet, the decreased regional specialization in good jobs that we document does not have an obvious analogue in the inequality literature. To understand these developments more fully, we turn next to analysis of the regional dynamics of growth in good jobs.

4 Changes in Spatial Distribution of Good Jobs

In this section, we study whether good jobs have become more or less concentrated in the regions in which they were initially agglomerated, and whether regions that were initially more specialized in good jobs have seen their specialization rise by more or less than other regions. The first exercise helps us understand whether over time employment in good jobs tends to spatially concentrate (suggesting stronger agglomeration effects) or to spatially disperse (suggesting stronger congestion effects); the second exercise helps us understand how other sectors adjust over the longer run to changes in local employment in good job industries. We begin by examining all workers, then separate workers according to college attainment, and finally examine patterns according to worker gender, nativity, and race.

4.1 Share of Good Jobs

A key question to understand the changes in the geography of work in the US is whether jobs in general and well-paid jobs in particular tend to spatially concentrate or disperse over time. In this section, we use a simple framework to address changes in the spatial distribution of good jobs and then present our empirical results, before extending the framework in the next section to changes in regional specialization in good jobs.

To assess changes in the location of good jobs over the last four decades, we estimate the following regression separately for the 1980-2000 and 2000-2021 periods:

$$\ln Share^{g}_{ct} = \alpha + \beta \ln Share^{g}_{ct-1} + \epsilon_{c,t} \tag{4}$$

where $Share^{g}_{ct}$ is the value in equation (2) (i.e., the share of CZ c in national employment in good job industries in year t), and $\epsilon_{c,t}$ represents shocks to good job industries in CZ c over the period $t-1$ to t. The parameter β characterizes how the change in the share of good jobs between $t-1$ and t relates to the initial level in $t-1$. In the case of the regression for the 2000-2021 period, for example, finding that $\beta < 1$ would indicate that CZs with a larger initial share of good jobs in 2000 experienced smaller relative gains in good jobs and ended up with a lower share in 2021, while CZs with a small initial share of good jobs experienced faster growth and ended up with a larger share. This scenario would imply catchup of smaller regions to larger regions, or regression to the mean in the spatial concentration in good jobs, as broadly consistent with the spatial model of innovation and diffusion in Duranton and Puga (2001).[32] Such a pattern could indicate that capital tends to flow toward CZs with cheaper factors of production—lower costs of land and labor—and (or) that agglomeration economies are weak in the tradable industries that account for most good jobs.[33]

[32] Relatedly, Duranton (2007) finds that narrowly defined industries tend to reallocate across regional labor markets over time, possibly suggesting mean reversion in regional industry concentration.

[33] Mean reversion in values may be consistent with convergence, divergence, or stability in the spatial distribution of good job shares across CZs (Quah, 1996). In Figures A10 and A11, we plot kernel densities for the spatial distribution of CZ good job shares and CZ specialization in good jobs, respectively, for 1980, 2000, and 2021. The distribution of good job shares appears to be stable over time, broadly consistent with Duranton (2007); the distribution of CZ specialization in good jobs appears to have become mildly more

On the other hand, finding that $\beta > 1$ would imply that CZs with a larger initial share of good jobs in 2000 tended to experience larger relative employment gains and ended up with an even higher relative share in 2021, which would imply momentum in the location of good jobs or the opposite of catch-up. This scenario would imply increasing geographical inequality across CZs, due to good jobs tending to concentrate spatially over time, as would be consistent with agglomeration economies being stronger determinants of the location of good jobs than production costs (Moretti, 2012; Diamond, 2016; Davis and Dingel, 2019). Finally, finding that $\beta = 1$ would be consistent with proportional growth in good job industries (Gabaix, 2009), such that any shock that caused a CZ's share of good jobs to rise or fall would lead to a persistent increase or decrease in that CZ's share of good jobs.

4.1.1 All Workers

Figure 6 presents regression results for equation (4), with the 1980-2000 period shown in the left panel and the 2000-2021 period shown in the right panel. Each marker represents a CZ. CZs with an above-median share of employment in manufacturing in the initial year appear as red diamonds, while those with a below-median manufacturing share appear as blue circles. The names of the ten CZs with the largest increases in good job shares are written in green beside their markers, while the names of the ten CZs with the largest decreases in good job shares appear in red. The figures plot OLS best-fit lines, where we weight by the CZ working-age population (ages 18-64) in the initial year.

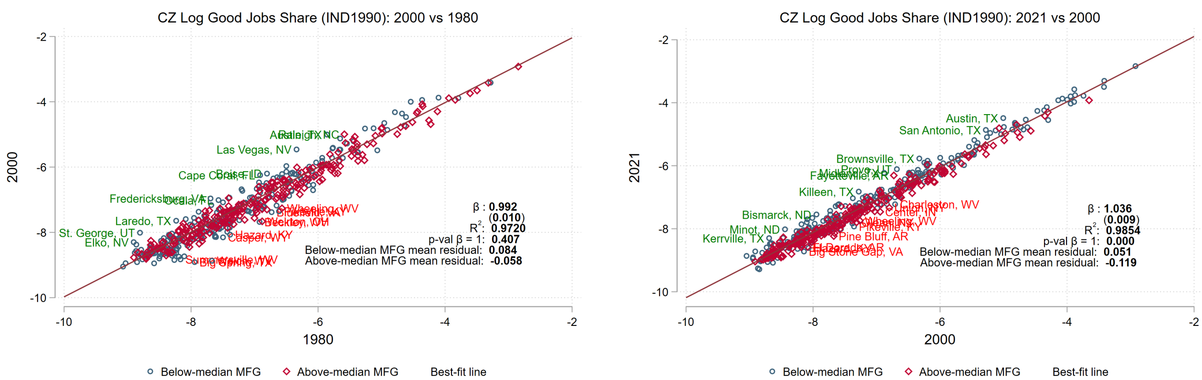
Consider first results for the 1980 to 2000 period in the left panel. The slope of the line is 0.992 (σ = 0.010) and is not statistically different from 1 (p-value=0.41). The R^2 of 0.97 indicates that the 1980 share is an important determinant of the 2000 share. There appears to be strong persistence in good job shares over the 1980-2000 period, consistent with growth in good jobs that is exactly proportional to the initial level and with findings in Gabaix (1999) for the distribution of city size in the US. Put differently, places that begin with large concentrations of good jobs tend to keep them, and vice-versa.

Results for the 2000-2021 period appear in the right panel of Figure 6. The picture that emerges is different from the earlier period since the slope is 1.036 (σ = 0.009) and statistically different from 1 at any conventional level of significance (p-value=0.001). As discussed above, a slope larger than 1 is consistent with divergence in the geographical location of good jobs. It suggests that spatial inequality across CZs increased between 2000 and 2021. Quantitatively, the implied increase in the spatial concentration of good jobs is not large. Our estimate indicates that if CZ A had a 10 *ppt* larger concentration of good jobs than CZ B in 2000, by 2021 CZ A would have had a 10.4 *ppt* larger concentration than

concentrated over time, consistent with the regression results we report in Section 4.2.

B (holding constant the total number of good jobs in the US).

Figure 6: Changes in CZ Good Job Shares: 1980-2000 and 2000-2021



Notes: The graphs plot CZ log good job shares in 2000 (y-axis) against CZ log good job shares in 1980 (x-axis) in the right panel, and for 2021 against 2000 in the left panel. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases are named in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

It is also apparent in Figure 6 that changes in good job shares depend on the importance of manufacturing for the local economy, consistent with findings in Section 3.2. CZs with an above-median initial share of employment in manufacturing (as indicated by red diamonds) tended to experience more negative changes in good job shares in comparison to CZs with the same initial share of good jobs but a below-median initial share of employment in manufacturing (as indicated by blue circles). For the 1980-2000 period, the weighted average of OLS residuals is 0.08 for CZs with above-median manufacturing share and -0.06 for those with below-median manufacturing share, indicating logically that the manufacturing decline hurt CZs specialized in manufacturing. For the 2000-2021 period, the corresponding averages are 0.04 and -0.11, respectively. Further, in both time periods most of the CZs with the largest increases in good job shares had below-median initial manufacturing shares (e.g., Fredericksburg, VA, and Las Vegas, NV, over 1980 to 2000; Austin, TX, and Provo, UT, over 2000 to 2021), while most CZs with the largest decreases in good job shares had above-median initial manufacturing shares (e.g., Warren, OH, and Wheeling, WV, over 1980 to 2000; Pine Bluff, AR, and Union, NY, over 2000 to 2021).

One might think that systematically more negative changes in good job shares in initially more manufacturing oriented CZs would work against the strong persistence in good job shares that we see in Figure 6. Closer inspection reveals that for any given level of initial good jobs shares, contracting shares in more manufacturing oriented CZs appear to be approximately offset by expanding shares in less manufacturing oriented CZs, such that the reallocation in good jobs from manufacturing to non-manufacturing occurred largely within size classes of commuting zones. Manufacturing CZs that lost good jobs appeared to lose them for good (Gagliardi et al., 2023; Autor et al., 2024), while non-manufacturing CZs that gained good jobs tend to gain them for good.

Figure 7: Changes in CZ Good Job Shares in Top Tercile CZs, 1980-2000 and 2000-2021

Notes: The graphs plot CZ log good job shares in 2000 (y-axis) against CZ log good job shares in 1980 (x-axis) in the right panel, and for 2021 against 2000 in the left panel. We restrict the sample to CZs in the top third of good job shares in the initial year. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

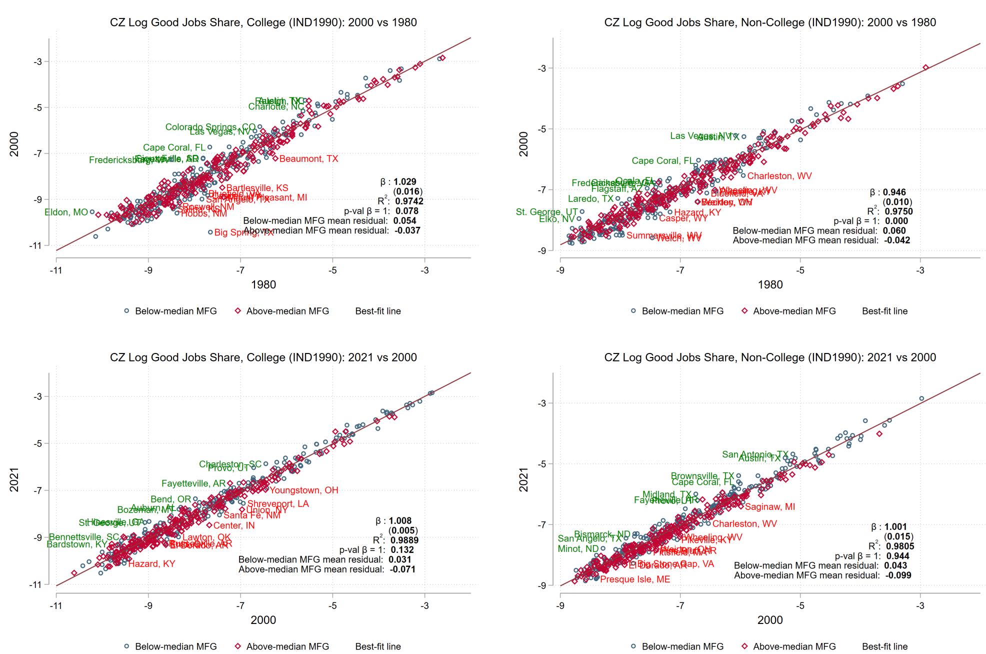
Because of their outsize role in wage growth and innovation nationally (Hsieh et al., 2019), we are especially interested in the experience of CZs that started near the top of the 2000 distribution of good jobs and whether the changes seen in the full sample are representative of the experience of the CZs initially most endowed with high-wage employment. To evaluate this group, Figure 7 repeats Figure 6, restricting CZs to those in the top one third of good job shares in the initial year. For these larger CZs, there is also strong persistence in good job shares: we easily fail to reject equality of slopes to 1 in either time period. Approximately offsetting effects of falling good job shares in manufacturing CZs and rising good job shares in non-manufacturing CZs within size groups is again apparent.[34] The reallocation of good jobs from manufacturing to non-manufacturing CZs thus appears to be common across the size distribution of CZs, which explains how substantial reallocation of good jobs between CZs can be consistent with proportional growth in CZ good job shares.

[34]In unreported results, we find that figures are similar when we examine the top decile of CZs in terms of initial good job shares.

4.1.2 College versus Non-College Workers

Figure 8 repeats the plots in Figure 6, separating workers by education level. In constructing these plots, we estimate equation (2) separately for workers with and without a BA degree, such that the definition of good jobs is now specific to college attainment. Note that because the definition of good jobs now differs for workers with and without college, the slope coefficient for all workers in a given time period in Figure 6 is not by construction a weighted average of those for college and non-college workers for the same time period in Figure 8.

Figure 8: Changes in CZ Good Job Shares by Education, 1980-2000 and 2000-2021



Notes: The graphs plot CZ log good job shares in 2000 (y-axis) against CZ log good job shares in 1980 (x-axis) in the top row, and for 2021 against 2000 in the bottom row. Results for workers with (without) a BA degree are in the left (right) panels. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in in the initial year.

For the 1980-2000 period, the slope coefficient is 1.029 ($\sigma = 0.016$) for workers with college, implying modest momentum or pressure for divergence in the location of good jobs for the more educated, and 0.946 ($\sigma = 0.010$) for workers without college, suggesting mean reversion or convergence in the location of good jobs for the less educated. This pattern is consistent with the notion that agglomeration economies are (mildly) stronger in more human-capital-intensive industries (e.g., Davis and Dingel, 2019; Moretti, 2021). In the more recent 2000 to 2021 period, the slope coefficients are similar for college-educated and non-college-educated workers and statistically indistinguishable from 1 (p-values equal 0.132 for college workers and 0.944 for non-college workers), indicating stability in spatial inequality of good jobs. For both education groups and in both time periods, we see that growth in good jobs was stronger in CZs that were less manufacturing oriented and weaker in those that were more manufacturing oriented, just as in Figure 6.[35]

4.1.3 Gender, Nativity, and Race

There is substantial interest in the literature in how individuals have been differentially affected by recent economic shifts according to their demographic characteristics. In terms of gender, the evidence indicates that recent shifts in the US economy have favored traditionally female-dominated occupations relative to traditionally male-dominated ones. Because non-college men are overrepresented in manufacturing, for instance, they have been more exposed to job loss caused by rising import competition from China (Autor et al., 2019). In addition, the rising college attainment of women relative to men (Goldin, 2014) may have given women better access to good jobs in industries that require high levels of schooling. At the same time, males continue to be overrepresented in the "greedy occupations" that predominate in select high-wage industries, including consulting, finance, IT, and specialized medicine (Goldin, 2014; Goldin et al., 2017; Cortés and Pan, 2023). Changes in the location of good jobs for women thus may differ from that for men.[36]

Nativity is an additional source of differential exposure to changes in regional economic conditions. Among the highly educated, foreign-born workers are more likely than the native-born to have STEM training (Hunt and Gauthier-Loiselle, 2010; Hunt, 2011) and to work in high-tech industry clusters (Peri et al., 2015); among the less educated, the foreign-born are overrepresented both in high-wage construction (Cadena and Kovak, 2016) and in low-wage agriculture, hospitality, and personal services (Hanson et al., 2017). The stronger migration responsiveness of the foreign-born over the native-born to local shocks (Borjas, 2001; Cadena and Kovak, 2016) may account for why immigrants are overrepresented in regions with new and expanding industries (Morris-Levenson, 2022). Immigration policy may also play a significant role in immigrant settlement patterns. Temporary work visas for

[35]Figure A12 replicates Figure 8 for the subset of CZs in the top tercile of the 2000 distribution of shares of good jobs. The left panel shows a pattern consistent with the one observed for college graduates in the full sample, namely a slope very close to 1 and a general persistence in national job shares over time. As in the case of the full sample of CZs, declines in good job shares from 2000 to 2021 are more prevalent among CZs with above-median manufacturing shares. The right panel uncovers a slope above 1 for less educated workers, in contrast to what we observed in the full sample. Thus, among CZs with a large initial share of good jobs, gains in good jobs for less-educated workers were larger in CZs with an larger initially shares, suggesting divergence in the location of good jobs for this group.

[36]On the other hand, assortative mating (Greenwood et al., 2014) may work against such differences by reinforcing the exposure of similarly educated men and women to common regional economic shocks.

highly educated workers, such as the US H-1B program, may differentially select immigrants whose skills match current employer demands (Kerr and Lincoln, 2010; Peri et al., 2015), leading foreign-born workers to abound in places with stronger job growth in higher-wage positions (Kerr et al., 2016). Nativity may also affect access to opportunity via migration networks. Whereas the strong majority of young native-born adults reside within 100 miles of where they lived as children (Sprung-Keyser et al., 2023), foreign-born location choices may reflect the happenstantial location of migrant enclaves established in earlier decades (Bazzi et al., 2020; Abramitzky et al., 2024). These enclaves may create migration links between relatively distant locations, possibly causing bilateral migration options to vary according to a worker's country of birth (Borusyak et al., 2022).

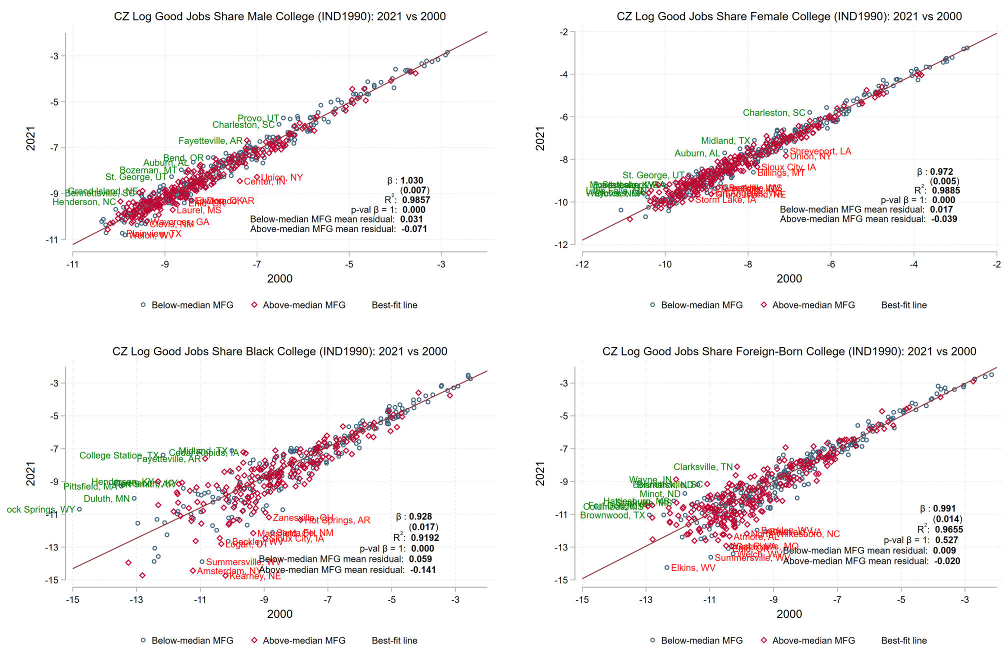
Black workers historically have been underrepresented in high-paying jobs and subject to other forms of wage discounts (Hsieh et al., 2019; Derenoncourt and Montialoux, 2021). The concentration of US manufacturing in the Midwest and Northeast, for instance, gave Black workers inferior access to jobs in the sector, until the Great Migration brought large numbers of Black households to the North, especially after World War II (Derenoncourt, 2022). Perhaps because Black workers who had found jobs in manufacturing by the 1970s were relatively recent hires, they were differentially hurt by manufacturing job loss in the 1980s arising from Japanese import competition (Borjas and Ramey, 1995; Batistich and Bond, 2023). Between 1950 and 1980, when US manufacturing relocated from large Northern cities to smaller towns in the region and new industrial cities in the South (Eriksson et al., 2021), places with larger non-Hispanic white populations benefited disproportionately. Correspondingly, the later impacts of globalization on local labor markets in the 1990s and 2000s, including the China trade shock, appeared to hurt white workers more than Black workers (Kahn et al., 2022; Autor et al., 2024). Further, Black workers continue to be overrepresented in fast-growing cities of the New South (Glaeser and Gottlieb, 2009). Consistent with these patterns, racial differences in intergenerational mobility for children born between 1978 and 1992 appear to be reducible to differences in economic conditions in the communities in which these children grew up (Chetty et al., 2024).

Motivated by these patterns, we examine the 2000 to 2021 changes in the location of good jobs for men versus women and then Black workers versus foreign-born workers.[37] The first row of Figure 9 presents results for workers with a college education over 2000 to 2021, with men in the left panel and women in the right panel. Whereas for all college workers in Figure 8 we obtain a highly precisely estimated slope coefficient very near unity ($\beta = 1.008$, $\sigma = 0.005$), a different picture emerges when we examine men and women separately. In Figure 9, we estimate $\beta = 1.030$ ($\sigma = 0.007$) for college men, consistent with mild divergence

[37]The corresponding 1980 to 2000 changes are reported in Appendix Figures A13 and A14.

in good job shares, and $\beta = 0.972$ ($\sigma = 0.005$) for college women, consistent with mild convergence in good job shares. It appears that good jobs for college-educated men have become slightly more spatially concentrated, while good jobs for college-educated women have become slightly more spatially dispersed.[38]

Figure 9: Changes in CZ Good Job Shares by Demographic Group, College: 2000-2021



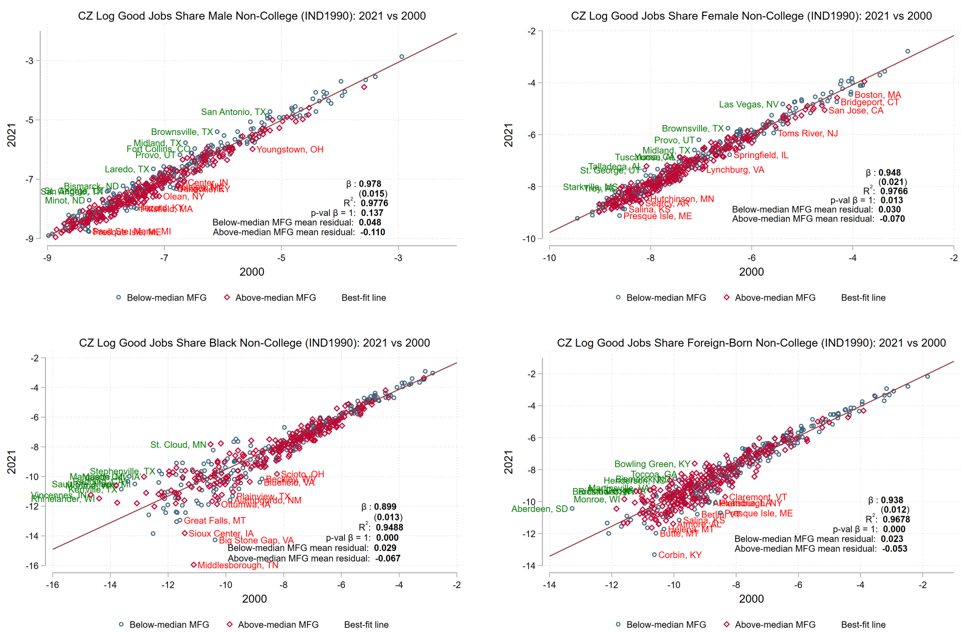
Notes: The graphs plot CZ log good job shares in 2021 (y-axis) against 2000 (x-axis) for workers with a BA degree. Samples are restricted to males workers (upper left), female workers (upper right), Black workers (lower left), and foreign-born workers (lower right). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in 2000.

The bottom row of Figure 9 shows Black workers in the left panel and foreign-born workers in the right panel (in each case for workers of either gender). For the former group, we see clear evidence of mean reversion. The slope coefficient estimate is 0.928 ($\sigma = 0.017$), which is well below 1 both economically and statistically. The more pronounced spatial diffusion of good jobs for Black college workers could reflect the accelerating catch-up by Southern CZs with thriving college-educated black populations, such as Atlanta, Charlotte, Houston, Nashville, and Raleigh-Durham. By contrast, we see little evidence of mean reversion for college-educated foreign-born workers. The slope for them is very close to 1 ($\beta = 0.991$, $\sigma = 0.014$), pointing to stability in the spatial distribution of good jobs for immigrant

[38]This may reflect differential patterns of specialization in good jobs by industry for men and women.

workers with a BA degree. This is surprising, perhaps, since even as the foreign-born in general have become more geographically dispersed across the US, the location of good jobs for this group has not spread but rather appears to be stable.

Figure 10: Changes in CZ Good Job Shares by Demographic Group, Non-College: 2000-2021



Notes: The graphs plot CZ log good job shares in 2021 (y-axis) against 2000 (x-axis) for workers without a BA degree. Samples are restricted to males workers (upper left), female workers (upper right), Black workers (lower left), and foreign-born workers (lower right). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in 2000.

Figure 10 replicates the analysis for workers without a college education. In all four cases (male, female, Black, and foreign-born non-college workers), the slopes are significantly smaller than in the previous figure, consistent with the earlier result of mean reversion for the full sample of non-college workers in Figure 8. For three of the four groups—all but non-college men—we easily reject a unit value of β. Mean reversion is strongest for non-college Blacks, for which $\beta = 0.899$ ($\sigma = 0.013$), which supports the notion that African American workers are the group that has experienced the most pronounced geographical spread in economic opportunity over the last two decades, irrespective of schooling. The historical over-representation of African Americans in more rapidly growing Southern states and under-representation in specialized manufacturing towns may be at work, here.

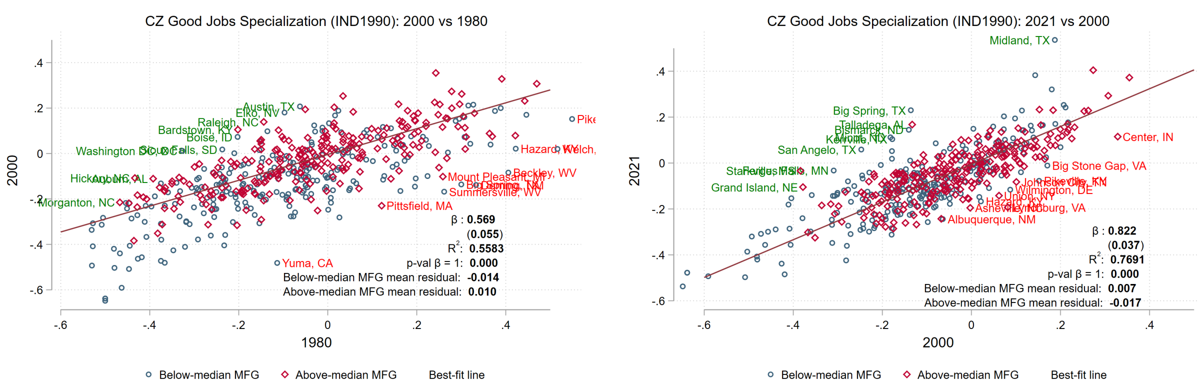
4.2 Specialization in Good Jobs

We now turn to our second outcome variable—CZ specialization in good jobs. We estimate the following regression, which is analogous to that in equation (4):

$$\ln Share^{g}_{ct} - \ln Share_{ct} = \tilde{\alpha} + \tilde{\beta}\left(\ln Share^{g}_{ct-1} - \ln Share_{ct-1}\right) + \tilde{\epsilon}_{c,t} \tag{5}$$

where for CZ c, $Share^{g}_{ct}$ is its period t share of employment in good job industries, $Share_{ct}$ is its period t share of employment in all industries, and $\tilde{\epsilon}_{c,t}$ represents shocks to specialization in good jobs in c over $t-1$ to t. As before, we estimate this regression separately for the 1980-2000 and 2000-2021 time periods. A finding of $\tilde{\beta} < 1$ in the 2000-2021 regression would imply mean reversion in good jobs specialization, or that between 2000 and 2021 CZs with a weaker initial specialization in good jobs experienced some amount of catch up while CZs with a stronger initial specialization became relatively less specialized. A finding of $\tilde{\beta} < 1$ would correspondingly imply momentum in specialization, or that more specialized CZs became even more specialized and less specialized CZs fell further behind.

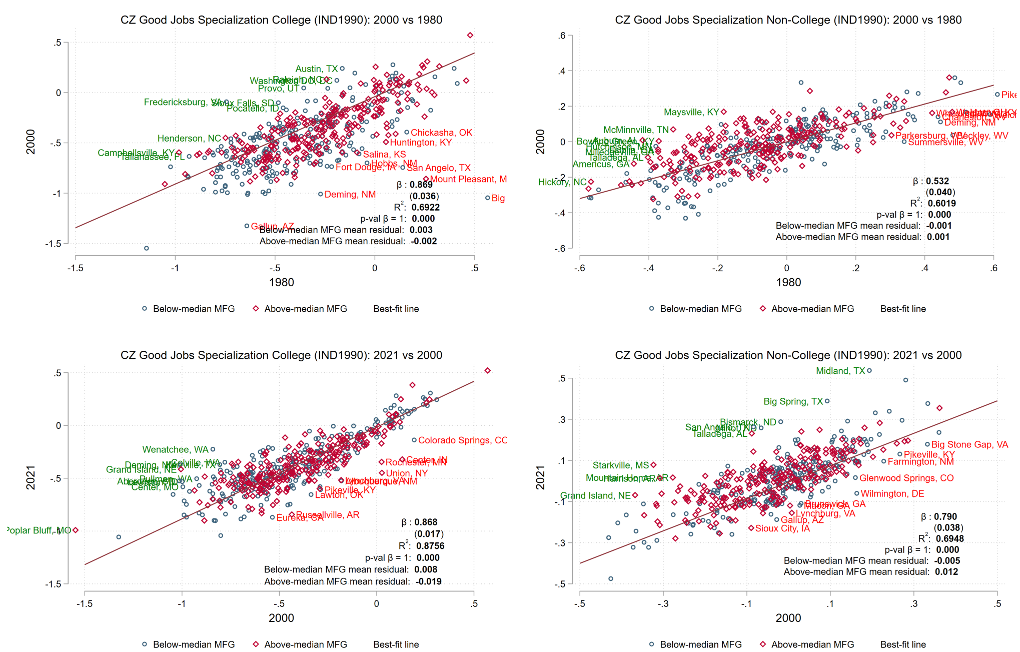
Figure 11: Changes in CZ Good Job Specialization, 1980-2000 and 2000-2021



Notes: The graphs plot CZ log good job specialization in 2000 (y-axis) against CZ log good job specialization in 1980 (x-axis) in the right panel, and for 2021 against 2000 in the left panel. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job are named in green, and for the 10 largest decreases are named in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure 11 shows results for the 1980 to 2000 period on the left and the 2000 to 2021 period on the right. The estimated slope coefficients are 0.569 ($\sigma = 0.055$) and 0.822 ($\sigma = 0.032$), respectively. Both are are far below unity statistically and economically, consistent with strong mean reversion over both time periods, with especially strong mean reversion during the earlier period. This finding implies a reduction in geographical differences in specialization in good job industries across CZs. To get a sense of the magnitude of convergence implied by our estimates, again consider CZs A and B, and assume that in 1980 A had a 10 *ppt* greater specialization in good jobs than B. The $\tilde{\beta}$ estimated in the earlier period indicates that by 2000 the difference in specialization would have been reduced by over two-fifths. The $\tilde{\beta}$ estimated in the later period, which points to less convergence, indicates that if in 2000 CZ A had a 10 *ppt* greater specialization in good jobs than CZ B, by 2021 the difference would have been reduced by about one-sixth.

Figure 12: Changes in CZ Good Job Specialization by Education, 1980-2000 and 2000-2021



Notes: The graphs plot CZ log good job specialization in 2000 (y-axis) against CZ log good job specialization in 1980 (x-axis) in the top row, and for 2021 against 2000 in the bottom row. Left (right) panels restrict the sample to workers with (without) a BA degree. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job are named in green, and for the 10 largest decreases are named in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

A qualitatively similar picture emerges when we split the sample by education (again, using industry fixed effects and good job definitions specific to the education group) in Figure 12. The slopes for college workers are 0.869 ($\sigma = 0.036$) for 1980 to 2000 and 0.868 ($\sigma = 0.017$) for 2000 to 2021, indicating a common degree of mean reversion in the two time periods. For non-college workers, by contrast, slopes rise from 0.532 ($\sigma = 0.040$) for 1980 to 2000 to 0.790 ($\sigma = 0.038$) for 2000 to 2021, indicating reduced by still substantial mean reversion in good job specialization. Interestingly, when we instead focus on the subset of CZ with the strongest initial specialization in good jobs, the picture that emerges is different.

Figure A15 shows changes in good job specialization over 2000 to 2021 for CZs in the top tercile and top decile of specialization in 2000. For non-college workers, the estimated slope coefficients are larger (relative to the full sample of CZs in Figure 12) but remain well below one. But for college workers, they are very close to unity: 1.019 ($\sigma = 0.039$) for top tercile CZs and 0.980 ($\sigma = 0.065$) for for top decile CZs. Thus, among the subset of CZs that were initially more specialized in good jobs, there is clear persistence in good job specialization for more-educated workers. This finding may reflect the enduring strength of regional innovation hubs that supply good jobs to college graduates (Kerr and Robert-Nicoud, 2020).

In Figure A16 we split the sample of college-educated workers by demographic group for 2000 to 2021. We find similar specialization dynamics for males and females. The strongest convergence is for Blacks workers, whose slope is only 0.275 ($\sigma = 0.048$), the flattest of any group in any time period. In Appendix Figure A17 we replicate the exercise for less educated workers and find a picture that is qualitatively similar.

4.3 Discussion

Our estimation results suggest that there is both strong persistence in the location of good jobs—places with larger concentrations of good jobs in earlier years tended to be those with larger concentrations in later years—and weakening specialization in good jobs—specialization in good jobs increased by more (less) in places that were initially less (more) specialized in good job industries. Regarding the first result, which is based on equation (4), for college males we estimate a value of β that is slightly larger than one, indicating momentum or divergence in good job shares, while for all other groups we estimate a value of β that is slightly less than one, indicating mean reversion or convergence in good job shares. These mild deviations from unity aside, the essential finding is one of near-proportional growth. Places that began with a larger number of good jobs, or equivalently that were subject to larger positive shocks to their good job industries (e.g., those more focused on non-manufacturing and less focused on manufacturing), tended to hold onto their relative levels of or gains in high-wage positions. Forces for the spatial dispersion of good jobs thus appear to be weak (with shocks to good job industries primarily responsible for their geographical reorganization). When we look at specialization in good jobs, which is based equation (5), we find evidence of strong mean reversion or regional convergence in both time periods. For all worker groups, the estimated values of $\tilde{\beta}$ are well below 1.

To understand the difference in findings for the two outcome variables, consider the developments for college males over the 2000-2021 period, when we see divergence in good job shares and convergence in good jobs specialization. An increase in a CZ's share of good jobs implies a gain in the number of good jobs in the CZ, *allowing the size of the local labor* *market to adjust*. By contrast, an increase in specialization implies a gain in good jobs, *holding constant the relative size of labor market*. Put differently, the latter "penalizes" CZs when overall size increases in response to an increase in good jobs.

To then see how it is possible for the share of good jobs to increase in a CZ while specialization in good jobs decreases, consider an exogenous shock to the absolute number of good jobs in the CZ's tradable sector. How specialization changes depends on the relative magnitude of the employment changes in good job industries and other industries that are ultimately created in the local economy. If the demand for non-tradable services is non-homothetic, and non-tradable services tend to be low-wage and labor-intensive—as is the case for restaurants, retail, many personal services, and many other parts of the non-tradable sector—then the affected CZ may add even more jobs in low-wage services, thereby reducing specialization. Moretti (2010), for example, estimates that the exogenous gain of 1 manufacturing job in an MSA causes the addition of 1.6 local service jobs in the same MSA within 10 years. While not all local service jobs are necessarily low-wage, the job multiplier exceeds 1 by a margin wide enough to be consistent with a decline in specialization.

Our findings are broadly consistent with the emphasis in Diamond (2016) and Diamond and Gaubert (2022) on the increasing role of consumption in the spatial agglomeration of more-educated workers after 1980. They are also reminiscent of the quantitative results in Couture et al. (2024), in which rising top-end incomes lead to the increased concentration of high-income individuals in downtown neighborhoods in which they are able to consume the non-traded services (e.g., bars, restaurants, nightlife) for which they have relatively strong demand. The difference here is that our results are suggestive of such a pattern *across commuting zones*, rather than *across neighborhoods* within a CZ.

An alternative, and not mutually exclusive, scenario is one in which the combined result of a CZ's share of good jobs increasing while its specialization in good jobs is decreasing is due to housing supply being inelastic in larger CZs (Baum-Snow and Han, 2024). With inelastic housing, any employment gains in one good job industry may be offset by employment losses in other, more labor-intensive good job industries, which are priced out of the local labor market. This appears to be what has happened in cities such as San Francisco, San Jose and Seattle, where the growth in labor demand in the high-tech sector raised the CZs' share national employment in good jobs industries (Hsieh and Moretti, 2019). Because the expansion of high-tech jobs also raised local housing prices and the overall cost of living (Diamond and Moretti, 2021), the ultimate result was lower employment in non-high tech tradable industries, such as manufacturing, since the wages needed to attract workers to these expensive CZs became too high for manufacturing employers to stay competitive with cheaper CZs. Immigration may play a role in how these expensive CZs are able to supply labor-intensive, non-traded services, since foreign-born workers appear relatively willing to reduce their housing consumption to access high-paying jobs (Albert and Monras, 2022).

5 Correlates of Growth in Good Jobs

We have uncovered systematic changes in the geographical location of good jobs in the US over the last four decades. We now turn to the question of what the correlates of such changes may be. Specifically, we ask which characteristics of CZs in 2000 are most predictive of changes in the share of (and specialization in) good jobs over the 2000-2021 period. We emphasize that this exercise is purely for descriptive purposes.

We regress the 2000-2021 change in the good job share (or specialization in good jobs) on a vector X_c of CZ characteristics in 2000, conditioning on the 2000 share of (or specialization in) good jobs and weighting by the CZ working age population in 2000:

$$\ln y_{ct} - \ln y_{ct-1} = \gamma X_c + \theta \ln y_{ct-1} + \mu_{c,t}. \tag{6}$$

For parsimony, we use definitions of the good job share and specialization in good jobs based on the full sample of workers that includes all education levels. To make elements of γ more easily interpretable, we use population-weighted z-scores for continuous variables, which allows one to compare magnitudes of the estimated coefficients.

The vector X_c includes a broad set of CZ covariates across eight categories: demographics (population size and density, shares of Black, Hispanic and foreign born residents); human capital (share of residents with a college degree, per capita number of public and private colleges and universities, presence of a research university and a PhD granting university, per capita number of BA degrees and STEM degrees awarded in a year); industry structure (share of employment in manufacturing, professional and scientific services, finance, or IT); taxes and regulations (top and median state personal income tax rates, state corporate tax rate, Wharton index of land use regulations, GOP presidential vote share); local public sector (share of public sector employment, whether CZ contains the state capital, presence of a Medicare-certified hospital, a VA hospital or a medical-school teaching hospital); local amenities (number of hot and cold days, coastal indicator, violent crime rate, four measures of air pollution, per capita number of bars and restaurants); structure and fragmentation of local government (whether government in largest city in the CZ is run by a town council/city manager or by a mayor/city council or has a town commission; number of municipalities, number of special governments, number of school districts); and measures of social capital (share of residents born in the state, ethnic diversity index, voter participation in presidential election, Penn State Social Capital Index, fraction of children ages 0–17 residing in single-parent households, supply of libraries as proxied by the per-capita number of librarians, and frontier history index (Bazzi et al., 2020)). Data are for the year 2000 or the closest year to that date. Whenever possible, variables are expressed in per capita terms by dividing by the CZ working-age population in 2000. See Appendix Section 6 for details on data sources and variable construction.

Table 2 reports estimates for the change in share of good jobs between 2000 and 2021, while Table 3 reports the corresponding estimates for the change in specialization in good jobs over the same period. The first column reports the coefficient in a model in which the 2000-2021 changes in the share of good jobs or specialization in good jobs is regressed only on its initial level. The coefficient is positive in Table 2—indicating that the gains in the share of good jobs are positively correlated with the initial levels—and negative in Table 3—indicating that the gains in specialization in good jobs are larger in CZ with lower initial levels. These findings confirm results in Section 4 regarding spatial divergence in the share of good jobs (at least in the pooled sample that includes all workers) and strong mean reversion in specialization in good jobs.

Due to the potential for multicollinearity with a large number of covariates, we estimate three variants of equation (6). In column 2, we include a small subset of the variables in X_c that, based on the existing literature, would seem ex-ante particularly likely to be correlated with gains in good jobs. Specifically, we include (a) population, since urban growth models predict that the size of the local labor market governs the relative strength of agglomeration forces (Duranton and Puga, 2020); and the share of Blacks, Hispanics, and foreign-born residents as key local demographics; (b) the share of college-educated adults, reflecting the notion that the level of human capital of the labor force is a key determinant of labor demand and ultimately economic growth (Glaeser and Maré, 2001; Gennaioli et al., 2013; Moretti, 2004a,b); (c) the share of manufacturing employment, since this is a period of significant trade-induced employment losses which have been shown to penalize CZs with an initially strong manufacturing base (Autor et al., 2013a); (d) the state top income tax rate, since a growing body of evidence has highlighted the discouraging effect of taxation on the geographical location of high-income earners (Bartik, 1992; Kleven et al., 2014; Moretti and Wilson, 2017) and the Wharton index of land use regulations, because inelastic housing supply elasticity tends to raise land prices (Glaeser and Gyourko, 2018) and make an area less affordable; and (f) local amenities—climate, coastal location, and violent crime—which have been shown to affect labor supply to a locality (Albouy, 2016).

In both Tables 2 and 3, the coefficient on population is negative, indicating slower growth in good jobs and smaller gains in good job specialization in larger cities. The positive coefficient on the shares of foreign born points to larger gains in both indexes in cities with

Table 2: Change in CZ Share of Good Jobs, 2000-2021

	(1) Initial Regression	(2) Subset Regression	(3) All Controls	(4) LASSO
Initial Share of Good Jobs	0.000979**	0.000778*	0.000337	
Demographics				
Log Population		-0.00105***	-0.00102***	-0.000167
Population Density			0.000696	0.000196
Share Black		-0.000230	-0.000443	
Share Hispanic		-0.000484	-0.000611**	
Share Foreign-born		0.00140**	0.00128**	
Human Capital				
Share College Educated		0.0000508	0.0000901	-0.000150*
Public Colleges (4 year)			0.00000862	
Private Colleges (4 year)			-0.0000539	
Carnegie Research University			-0.000576	-0.000195
Doctoral Program Indicator			0.000483*	0.0000702
BA degrees			0.0000230	
STEM BA degrees			-0.000128	
Industry Mix				
Manufacturing employment share		-0.000303	-0.0000530	0.0000295
Professionals/Scientific employment share			-0.000107	0.000132
Finance employment share			-0.000210	
IT employment share			0.000573	0.000378***
Taxes & Policies				
State top income tax rate		-0.0000101	-0.000627	
State median income tax rate			0.000656*	
State corporate tax rate			-0.00000436	
Land Use Regulations		0.000576*	0.000669***	0.000185***
GOP Presidential Vote Share			0.000427**	
Public Employment				
Public sector employment share			0.000149	
State Capital Indicator			-0.000196	0.000145
Medicare Certified Hospitals			-0.000134	0.0000551***
Veterans Hospitals			0.0000348	
Medschool Hospitals			-0.000138	
Amenities				
Hot Days		-0.000449	-0.000130	-0.000113***
Cold Days		0.000277	0.000614	
Coastal Indicator		-0.000232	0.000308	
Violent Crime		0.000192	0.000144	-0.0000587**
NO2 pollution			0.000142	-0.000119
Ozone pollution			0.000777*	0.000211
SO2 pollution			-0.000261	-0.0000783*
PM25 pollution			0.000101	-0.00000180
Bars and Restaurants			0.000299**	
Local Government				
Town Mayor + Council				
Town Council + Manager			-0.000227	
Town Commission			0.000470	
Local governments			0.000156	
Special governments			-0.000186	0.0000205
School governments			0.000288*	0.0000213
Share Special governments			0.000237	
Share School governments			-0.000361*	
Social Capital				
Share Born in-state			0.000375	-0.000171***
Ethnic diversity index			-0.0000954	
Percent voted			-0.000875***	-0.000144***
Social Index			0.000621***	
Share single parents			0.0000866	
Librarians			0.000123	
Frontier History index			0.000144	
Constant	0.000559*	0.000650**	0.000546	0.000377
Adjusted R^2	0.180	0.525	0.745	0.255

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports OLS regression results (with robust standard errors) for equation (6) using the change in CZ log good job share over 2000-2021 as the dependent variable. The sample is the 499 CZs with a population of at least 52,000 in 2000. Regressions are weighted by the CZ 18-64 population in 2000. See Appendix Section 6 for details on the regressors.

an initially large immigrant population. In Table 3, the coefficient on college share is positive as one may expect based on the literature. The state's top income tax rate is, as expected, a negative predictor of gains in good job specialization.

In both tables, column 3 presents estimates of equation (6) in which we include the full vector X, while results in column 4 are based on running an initial LASSO regression to select which variables to include. CZ population is included as a mandatory control. In Table 2, the LASSO-based specification indicates that the IT employment share, land use regulations, and the number of Medicare-certified hospitals are positively correlated with gains in the share of good jobs, while the college share, the number of hot days, violent crime, SO2 pollution and two of the social capital proxies enter negatively. In Table 3, the LASSO specification indicates that population density, the employment share in professional and scientific services, the GOP vote share (which may proxy for pro-business leanings of local government) and the presence of a Medicare certified hospital (a likely source of good jobs) are positively correlated with gains in specializations in good jobs.

Some of these results are unexpected. Although a large body of evidence suggests that population growth since 1980 has been stronger in places with more educated workers, we find no evidence of these patterns when it comes to where good job industries have become more concentrated. If anything, the share of the adult population with a BA degree enters negatively in Table 2. The small and insignificant coefficient on the initial manufacturing share in both tables is puzzling, given that the period under consideration is one in which manufacturing hubs tended to experience large negative labor demand shocks. Contrary to our priors, the level of state taxes appear orthogonal to gains in the share of good jobs, while land use regulations enter positively, suggesting that a less elastic housing supply is correlated with larger gains in the share of good jobs. Given existing evidence that more stringent land use regulations limit housing supply (Glaeser and Gyourko, 2018), this finding may reflect the presence of omitted variables. The political economy of land use regulations is such that wealthier municipalities tend to be overrepresented among the localities that adopt strong land use regulations.

Overall, the picture that emerges from Tables 2 and 3 is a mixed one. Taken literally, the estimates would suggest that the correlates of good jobs growth are quite different from the well-established correlates of regional population growth. We stress however that the interpretation of these two tables is not straightforward. While long, the vector X_c likely includes only a subset of determinants of good job growth. Almost certainly, there are important determinants we are omitting. We thus again emphasize the analysis in this section should be interpreted as descriptive. Additionally, some of the variables in X_c may be subject to significant measurement error. As one example, social capital is difficult to

Table 3: Change in Specialization in Good Jobs, 2000-2021

	(1) Initial Regression	(2) Subset Regression	(3) All Controls	(4) LASSO
Initial Specialization	-0.0252***	-0.0266***	-0.0419***	-0.0419***
Demographics				
Log Population		-0.0336***	-0.0164	-0.00763
Population Density			0.0112	0.0218**
Share Black		0.00608	0.0128	
Share Hispanic		-0.000597	-0.00322	
Share Foreign-born		0.0422***	0.0422***	
Human Capital				
Share College Educated		0.0198**	-0.000288	-0.00625
Public Colleges (4 year)			0.00301	
Private Colleges (4 year)			-0.00329	
Carnegie Research University			-0.00593	0.00369
Doctoral Program Indicator			0.00972	-0.00843
BA degrees			-0.00747	
STEM BA degrees			0.00325	
Industry Mix				
Manufacturing employment share		0.00801	0.0195***	
Professionals/Scientific employment share			0.0321	0.0284*
Finance employment share			-0.00583	
IT employment share			0.00594	0.00879
Taxes & Policies				
State top income tax rate		-0.0163**	-0.0166	
State median income tax rate			0.0118	
State corporate tax rate			-0.0209***	
Land Use Regulations		0.00571	0.0104	-0.00720
GOP Presidential Vote Share			0.0105*	0.0258***
Public Employment				
Public sector employment share			0.00455	
State Capital Indicator			0.0130	
Medicare Certified Hospitals			0.00410	0.00991***
Veterans Hospitals			0.000536	
Medschool Hospitals			0.00392	
Amenities				
Hot Days		-0.00594	-0.0223	
Cold Days		-0.0141	-0.00128	
Coastal Indicator		0.00642	0.0128	0.00543
Violent Crime		0.00577	0.00959**	
NO2 pollution			0.00208	-0.00464
Ozone pollution			-0.00836	0.00323
SO2 pollution			0.00784	
PM25 pollution			-0.00138	-0.00284
Bars and Restaurants			0.00626	
Local Government				
Town Mayor + Council				
Town Council + Manager			0.000818	
Town Commission			-0.00342	
Local governments			0.00515	
Special governments			-0.00155	-0.00338
School governments			0.00346	
Share Special governments			0.00699	
Share School governments			0.00822	
Social Capital				
Share Born in-state			0.0323***	
Ethnic diversity index			0.00346	
Percent voted			0.00215	
Social Index			0.0131	
Share single parents			-0.0279***	
Librarians			-0.000785	
Frontier History index			0.00324	
Constant	-0.00294	-0.00546	-0.0156	-0.0111
Adjusted R^2	0.121	0.281	0.457	0.288

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports OLS regression results (with robust standard errors) for equation (6) using the change in CZ log good job specialization over 2000-2021 as the dependent variable. The sample is the 499 CZs with a population of at least 52,000 in 2000. Regressions are weighted by the CZ 18-64 population in 2000. See Appendix Section 6 for details on the regressors.

quantify and the variables we use are imperfect proxies at best. In this case, finding a coefficient not statistically different from zero may primarily reflect attenuation bias.

6 Discussion and Directions for Future Work

Much attention has been devoted to studying the growing geographical differences in wages and incomes across US cities and regions. Our analysis seeks to complement the existing literature by documenting changes in the spatial distribution of industries that pay high wages, as opposed to changes in the spatial distribution of workers who earn high wages. The two concepts are clearly related, but they are not identical. Some of the patterns that we uncover are expected given the existing literature, while others are more surprising.

We focus on a period of momentous changes in the US labor market. Over the last four decades, the industries that generate good jobs for American workers changed in profound ways. The two most important shifts that we document were the decline of good jobs in manufacturing and the rise of good jobs in human capital-intensive service industries. Between 1980 and 2021, the share of good jobs held by manufacturing workers was cut in half. This decline was caused by the collapse in the overall size of the manufacturing sector, not the relative decline of manufacturing wages, as the share of good jobs within manufacturing remained surprisingly stable. During the same period, the share of good jobs in business and professional services quadrupled, both because the sector's employment expanded and because an increasing fraction of its workers earn high salaries.

These nationwide industry shifts had important and well-documented impacts on local communities. Their overall effect on the geography of good jobs was complex. We find that over the last 40 years, CZs with an initially strong manufacturing base experienced smaller gains in good jobs than CZs with an initially weak manufacturing base. This is not particularly surprising and is in line with the wealth of evidence on the negative consequences of the the demise of factory employment on former manufacturing hubs. However, despite this trend, we also find that the shape of the spatial distribution of good jobs did not change significantly over this period, because the industry-specific shifts in labor demand created a roughly equal number of winners and losers within each equally-sized set of commuting zones. The net result is a remarkable stability in the geographical distribution of good jobs. More precisely, between 1980 and 2000, we find that growth in good jobs in a CZ is exactly proportional to its initial level, while between 2000 and 2021, we find that growth in good jobs was slightly faster in CZs with a higher initial level of good jobs. The latter finding suggests a mild increase in the spatial concentration of good jobs, which is slightly more pronounced for college graduates between 2000 and 2021. Quantitatively, however, the implied increase in the spatial concentration is modest. Our estimates suggest that a 10 *ppt* larger share of good jobs in 2000 is associated with a 10.4 *ppt* larger share in 2021. This finding is particularly surprising in light of the established evidence in the literature of a strong divergence in wages and earnings across cities and states over the last four decades. The evolution of CZ specialization in good jobs presents a clear picture of spatial convergence: between 1980 and 2021, specialization in good jobs increased by more in CZs that were initially less CZs specialized in good job industries.

We interpret the general stability of the spatial distribution of good jobs combined with the increased diffusion of specialization in good jobs as evidence that areas that experience gains in good jobs in the tradable sector tend to experience even larger endogenous gains in the demand for non-tradable, labor-intensive services. Alternatively, our findings are also consistent with the existence of some inelastically supplied non-traded factor of production—most likely land—that constrains total employment growth in areas that experience gains in good jobs in the tradable sector. The increased scarcity of land (or more presicely, buildable land) implies that employment gains in one good job industry need to be offset by employment losses in other good job industries, which are priced out of the local labor market. Such churning has received little attention in the literature.

These two explanations are clearly not mutually exclusive and their relative importance is likely to vary across localities as a function of the specific industry mix in the tradable sector and the local elasticity of housing supply. Future research should provide more direct evidence on the empirical relevance of these two explanations, and their relative importance both for the US as a whole and for specific commuting zones and regions.

Irrespective of the precise channel, our findings show that the spatial convergence in the specialization of good jobs was most consequential for Black, Hispanic, and foreign-born workers. Relative to the national average, these groups were overrepresented in Southern and Western cities that have experienced some of the fastest rates of convergence in good job specialization. As a consequence, the parts of the US that are rich in good jobs today look vastly different than those in 1980: they are more centered around human-capital-intensive tradable services, are surrounded by larger concentrations of low-wage, non-tradable service industries, and are more demographically diverse. These patterns of differential changes in geographic access to good jobs by race, ethnicity, and place of birth are understudied in the literature (relative to their importance) and may have implications for the optimal design of place-based policies along dimensions that the existing research has yet to investigate and would be helpful for future researchers to consider.

Additionally, it would be helpful to assess whether the stability of the spatial distribution of good jobs and the increased diffusion of specialization in good jobs that we uncover in our data are specific to the US or are observed in other high-income countries. Many of the labor demand shifts across industries that we find in the US—the decline of manufacturing and the rise of human capital-intensive services—also took place in Europe and East Asia, among other regions. But their effects on the distribution of employment across local labor markets appear more pronounced in the US than in European nations and Japan (Gagliardi et al., 2023). Understanding how the geography of good jobs has changed outside the US would be a fruitful direction for future research.

Among the many issues we are unable to explore are changes in the selection of high-wage workers (i.e., those with larger estimated worker fixed effects) into high-wage firms (Haltiwanger et al., 2024). Existing literature documents that high-wage workers and high-productivity firms differentially select into high-wage regions (Diamond, 2016; Gaubert, 2018) and that within these regions the former tend to be employed in the latter. The ultimate implications of these sorting patterns for local labor markets and specific groups of workers within local labor markets are an area where future work should focus.

Above all, our findings point to the need for a better understanding of the determinants of the location of goods jobs. We were unable to uncover a clear picture of the commuting zone characteristics and local policies that are correlated with the growth of good jobs, let alone the characteristics and local policies that cause the growth of good jobs. Future researchers should focus on improving our understanding of this puzzling question.

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Data Appendix: Variables used in the regression analysis

Below we describe the sources for the variables used in the estimation of equation (6), which is discussed in Section 5.

Demographics and Industry Mix. Demographic and labor market characteristics are from the 2000 Census. Ethnic fractionalization is calculated using data aggregated from IPUMS NHGIS time-series tables, based on the proportions of six Census-defined racial and ethnic groups.

Human Capital. We use the IPEDS Completions Survey to measure the number of BA degrees and the number of BA degrees in STEM fields. The numbers of two and four-year institutions of higher education in 1990 and 1996 are from Currie and Moretti (2003).

Taxes Policies. State tax rates and effective corporate income tax rates are from Moretti and Wilson (2017). Land use regulations are from the 2008 Wharton Land Use Regulation Index (Gyourko et al., 2019), crosswalked to CZs using a city name-CZ crosswalk. Eight cities in the index are not listed in the crosswalk, and are excluded from calculations; if a CZ has more than one city listed in the index, we calculate a population-weighted average of the cities within that CZ.

Public Employment. Counts of Medicare-certified hospitals, veteran hospitals, teaching hospitals, and hospitals with residency programs are from the 2001 Area Health Resource Files (AHRF).

Amenities. Weather and climate variables are from NOAA's nClimDiv database. Pollution variables do not have complete geographic coverage. We impute missing values for non-SO2 pollution with the minimum value in the state, and missing values for SO2 pollution with the CZ's state median SO2 pollution level. (Non-SO2 pollution is correlated with population; CZs with missing values generally have smaller populations). Crime data are from the FBI's Uniform Crime Reporting Program Data Series. Bar and restaurant data from the County Business Patterns for 2000; we use number of establishments in NAICS 722410 "Drinking Places (Alcoholic Beverages)" and NAICS 722511 "Full-Service Restaurants." Sixteen counties are missing in the violent crime and bar and restaurant data, which we exclude from the aggregation to CZs.

Local Government. Data on local government fragmentation are from the Census of Governments for 2002. The measures include the percentage of school and special districts among all local governments, the number of such districts per 10,000 residents, the number of general governments per 10,000 residents, and the total number of local governments per 10,000 residents. Forms of government are classified using data from the ICMA Municipal Form of Government Survey; we record government types (e.g., Mayor-Council, Council-Manager, etc.) of the most populous city in each CZ.

Social Capital. The social capital index is based on the 1997 Penn State Social Capital Index (https://nercrd.psu.edu/data-resources/county-level-measure-of-social-capital/), which measures the prevalence of membership associations (religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, sport and recreation clubs, and membership organizations NEC). Election data are from Dave Leip's US Atlas of Presidential Elections (https://uselectionatlas.org/). The American frontier index is from Bazzi et al. (2020) and represents the number of years a CZ was situated on the US frontier. Data on libraries are from the Institute of Museum and Library Services 2000 Public Library Survey.

Appendix Tables

Table A1: Summary Statistics for Full-time, Prime-age Workers, 1980-2021

	1980	2000	2021
Female	0.358	0.434	0.450
College	0.123	0.210	0.263
Below High School	0.179	0.096	0.068
Foreign-born	0.068	0.122	0.187
Hispanic	0.055	0.096	0.186
Black	0.097	0.103	0.121
Asian	0.019	0.040	0.071
White, Non-Hispanic	0.825	0.743	0.593
Manufacturing	0.280	0.183	0.119
Mean Earnings	48,218	62,778	70,403
Median Earnings	42,094	48,822	52,335
Equivalent Jobs	44,220,300	71,829,538	81,644,300
Raw Sample Size	2,211,015	3,503,348	3,503,936

Notes: Data are from the Census 5% sample for 1980 and 2000 and the ACS 5-year composite sample for 2017-2021 for 2021. Summary statistics are for full-time (at least 30 usual hours of work per week, at least 40 weeks worked last year), prime-age (ages 25 to 54) employed civilians (not living in group quarters) earning at or above the federal minimum non-farm wage in a given year (from FRED, using the 2017 minimum wage for 2021), applying Census and ACS sampling weights. Earnings are wage and salary income (INCWAGE). To address top-coding of earnings, we multiply 1980 top-coded values by 1.5, replace top-coded values in 2000 with mean earnings for values above the top code in the state, and replace top-coded values after 2010 with the 99.5^{th} percentile earnings in the state. Earnings are in 2021 USD based on the PCE deflator.

Table A2: Population and Employment in Sample CZs

	1980	1990	2000	2010	2021
Population Share, Sample	97.6	98.0	98.1	98.2	98.3
Population Share, Top Third	79.3	81.0	81.1	81.5	82.8
Population Share, Top Tenth	54.8	56.3	56.1	56.4	58.3
Employment Share, Sample	97.7	98.1	98.1	98.2	98.3
Employment Share, Top Third	80.2	81.7	81.5	82.0	83.3
Employment Share, Top Tenth	55.9	57.3	56.5	57.2	59.1

Notes: The sample we use for our analysis is the 499 commuting zones (out of 739 total CZs) with a total population of at least 52,000 residents in 2000. This table shows shares of national population and employment comprised by CZs in our sample based on data from the Census 5% sample for 1980 to 2000, the ACS 5-year composite sample for 2006-2010 for 2010, and the ACS 5-year composite sample for 2017-2021 for 2021. The first row shows the share of sample CZs in the US population in each year; the second row shows shares of the US population in CZs in the top tercile of good job industry employment (i.e., CZs whose share of national employment in good job industries is in the top one-third of all CZs); and the third row shows shares of the US population in CZs in the top decile good job industry employment (i.e., CZs whose share of national employment in good job industries is in the top one-tenth of all CZs). Rows four to six repeat the exercises for CZ shares of US total employment.

Table A3: Correlations in Industry Fixed Effects: Our Estimates vs. CRY

	Correlation Coefficient	N
4-digit industry codes	0.829	206
3-digit industry codes	0.843	89
2-digit industry codes	0.862	24

Notes: This table reports correlations in the industry fixed effects we estimate using OLS Mincer wage regressions for 2000 and those reported in Card et al. (2024) based on AKM regressions using LEHD data for 2008 to 2019. To compare our industry fixed effects estimates to theirs, we use industry employment weights to aggregate the 311 CRY industries (based on four-digit NAICS codes) to our 206 Census NAICS codes. We then repeat the exercise for industry fixed effects we estimate at the three-digit NAICS level (89 industries) and two-digit NAICS level (24 industries).

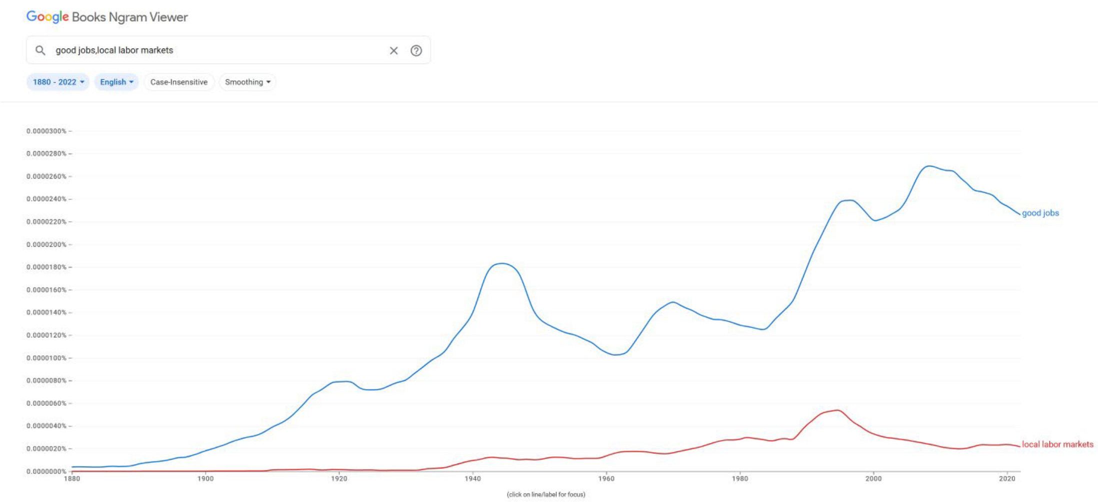
Table A4: Occupation Shares of Good Jobs by Sector

Occupation Title	Employment Share 1980	2000	2021
Agriculture/Mining/Utility/Construction			
Construction laborers (869)	6.4	9.6	14.6
Managers and administrators n.e.c. (22)	5.6	9.0	13.5
Carpenters (567)	10.5	11.1	8.6
Electricians (575)	4.3	4.6	5.6
Supervisors of construction work (558)	9.6	8.4	5.5
Manufacturing			
Managers and administrators, n.e.c. (22)	5.5	6.4	10.2
Assemblers of electrical equipment (785)	7.9	8.3	7.1
Machine operators, n.e.c. (779)	7.7	4.1	5.3
Production supervisors or foremen (628)	6.9	5.1	4.3
Sales workers (270)	2.1	2.7	3.1
Trade/Transport			
Driver/sales workers and truck drivers	14.5	17.3	20.7
Sales workers (270)	10.2	7.4	6.3
Managers and administrators, n.e.c. (22)	7.6	5.0	6.1
Sales supervisors and proprietors (243)	1.7	4.4	4.7
Mail carriers for postal service (355)	3.8	4.6	4.0
Finance/Professional/Legal Services			
Managers and administrators, n.e.c. (22)	11.1	7.9	13.3
Computer programmers (229)	3.1	9.2	12.3
Computer systems analysts and computer scientists (64)	2.6	8.3	11.0
Other financial specialists (25)	4.3	5.9	5.8
Management analysts (26)	2.7	5.2	5.2

Notes: This table reports the shares of employment in good job industries for five major sectors (shown in italics) that is accounted for by the five largest occupations for good jobs in that sector (e.g., in the Agriculture, Mining, Utilities, and Construction sector, the occupation of Construction Laborers (OCC1990 869) accounted for 9.6% of employment in good job industries in that sector in 2000). Good job industries are defined based on industry fixed effects from wage regressions for the year 2000. Occupations are defined using standardized OCC1990 codes, shown in parentheses. Employment data are from the Census 5% sample for 1980 and 2000 and the ACS 5-year composite sample for 2017-2021 for 2021.

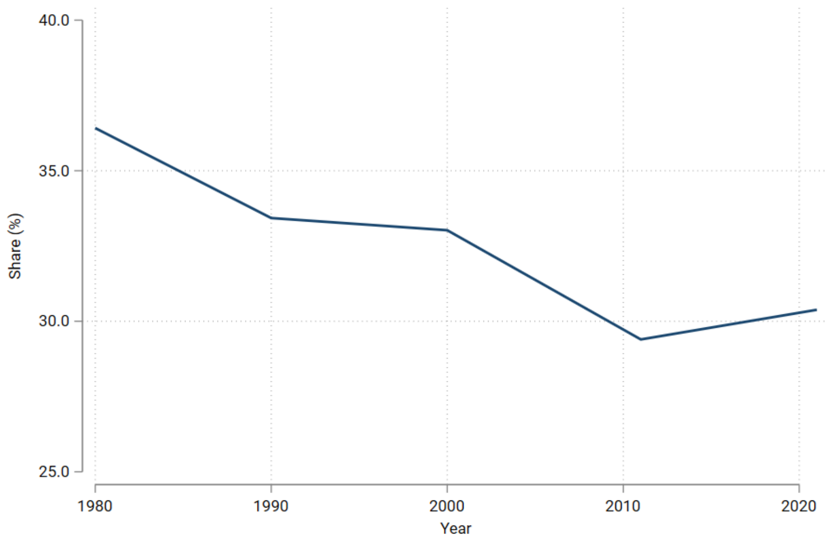
Appendix Figures

Figure A1: Google Ngram Mentions of ”Good Jobs” and ”Local Labor Markets”



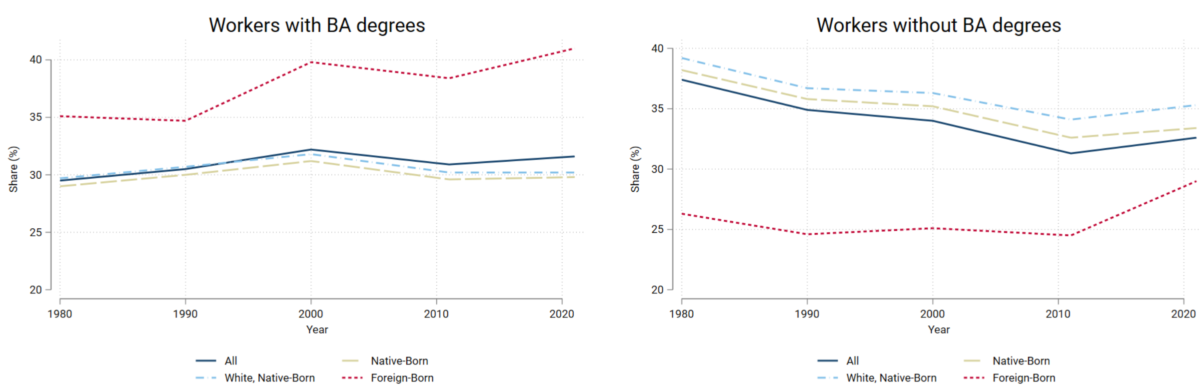
Notes: This figure plots frequencies of the phrases “good jobs” (shown in blue) and “local labor markets” (shown in red) from 1880 to the present in literature digitized by Google; frequencies were downloaded from Google Ngram on August 5, 2024.

Figure A2: Share of US Employment in Good Job Industries, 1980 to 2021



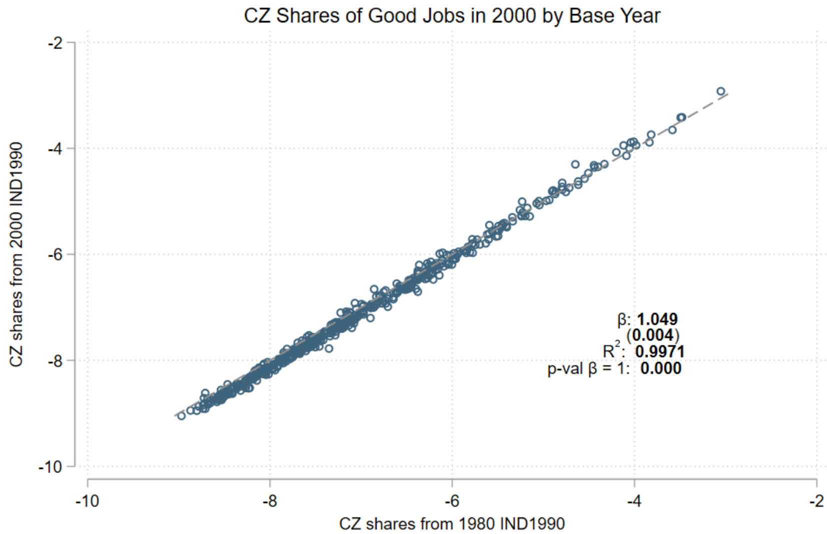
Notes: This figure plots the share of US employment of prime-age, full-time workers in good job industries, designated as those in the (employment-weighted) top tercile of estimated industry wage fixed effects for the year 2000 (such that by construction employment shares are one-third in that year).

Figure A3: Share of US Employment in Good Job Industries by Education, Race, and Nativity



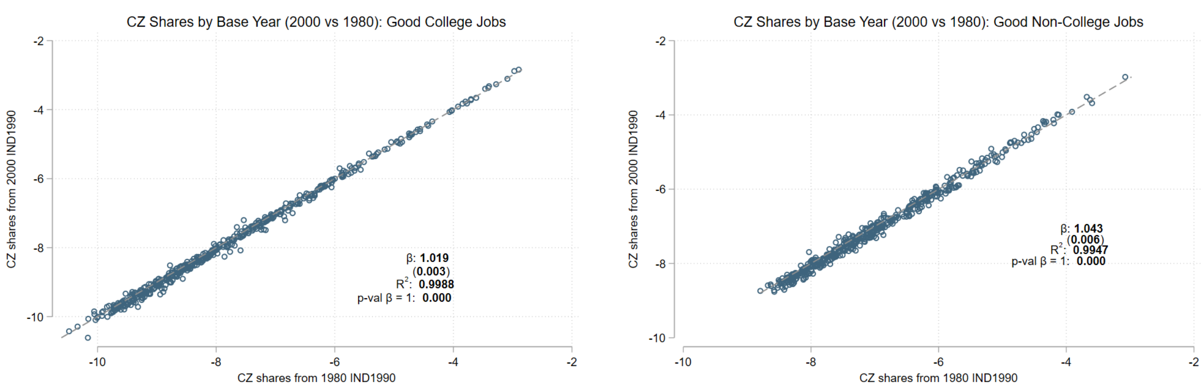
Notes: This figure plots the share of US employment of prime-age, full-time workers in good job industries by race and nativity group (see notes to Figure A2). The left panel includes workers with a BA degree; the right panel includes workers without a BA degree.

Figure A4: CZ Log Share of Good Jobs in 2000: 2000 vs. 1980 Industry Definitions



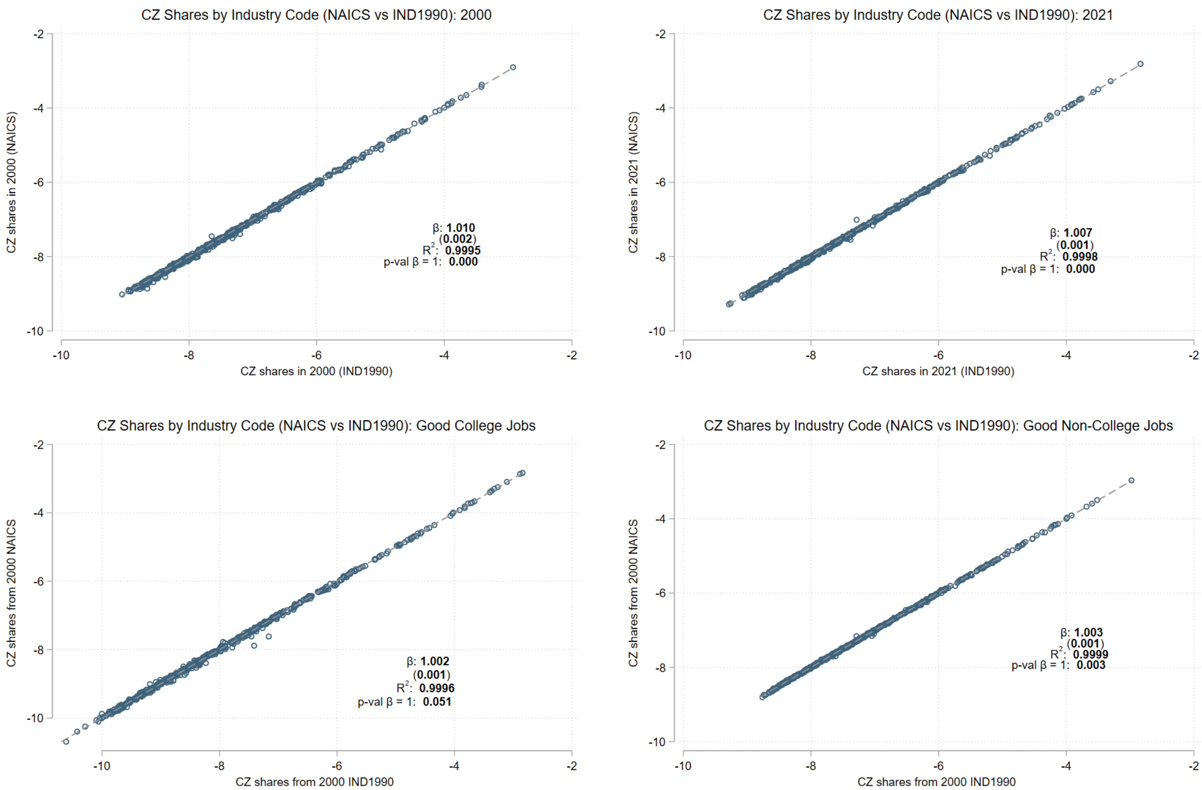
Notes: This figure plots the log CZ share of national employment in good job industries in 2000, using good job industries defined based on industry fixed effects estimated for the year 2000 on the vertical axis and for the year 1980 on the horizontal axis. The reported slope coefficient (and robust standard error) is based on an OLS regression weighted by the CZ 18-64 population in 2000.

Figure A5: CZ Log Share of Good Jobs by Education in 2000: 2000 vs. 1980 Industry Definitions



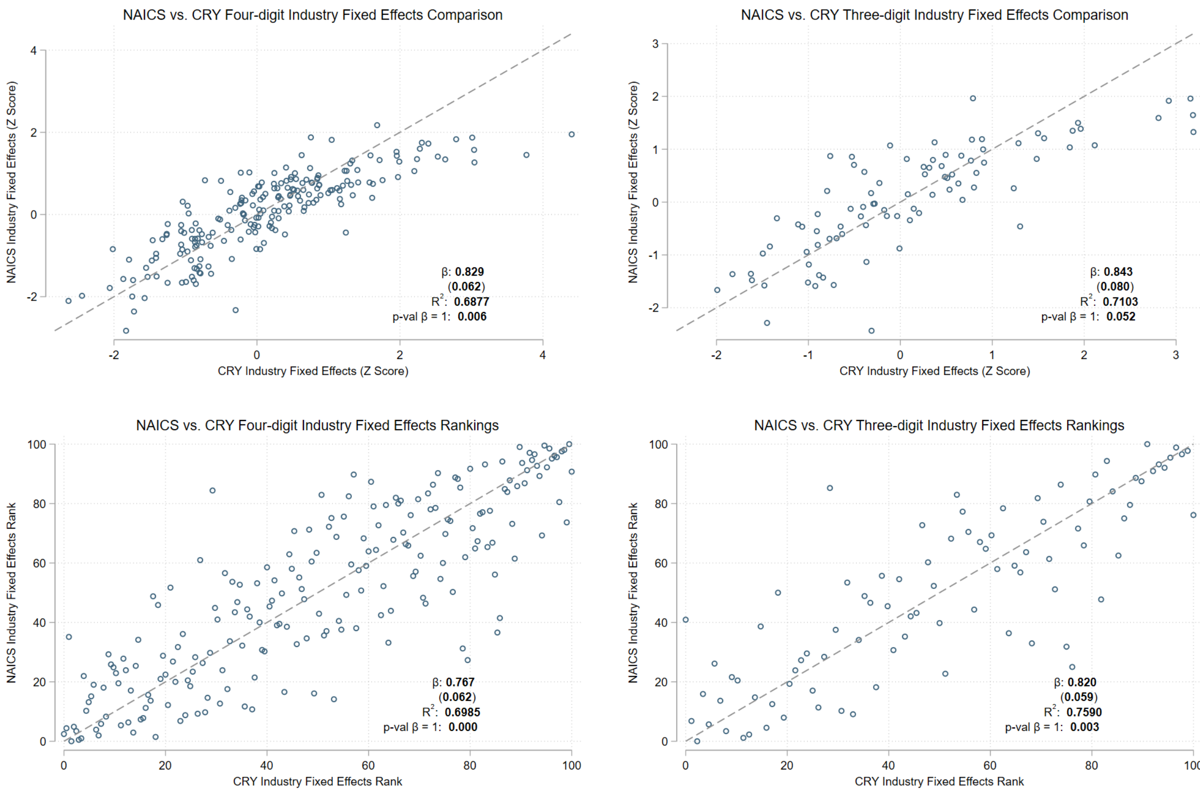
Notes: This figure plots the log CZ share of national employment in good job industries in 2000, using good job industries defined based on industry fixed effects estimated for the year 2000 on the vertical axis and for the year 1980 on the horizontal axis. We use good job industries defined separately by education group, with results for workers with a BA degree shown in the left panel and for workers without a BA degree shown in the right panel. The reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in 2000.

Figure A6: CZ Log Share of Good Jobs: NAICS vs. IND1990 Industry Definitions



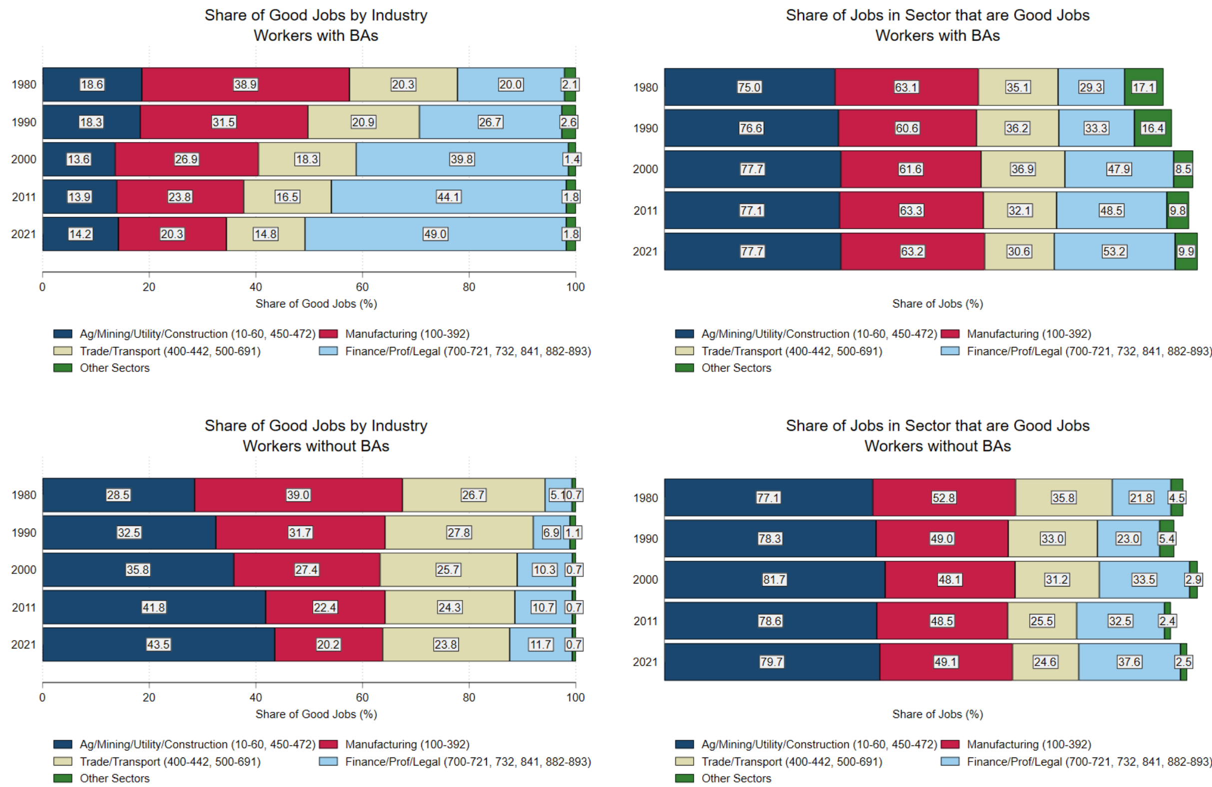
Notes: These figures plot the log CZ share of national employment in good job industries using good job definitions (for the year 2000) based on NAICS industry codes on the vertical axis and IND1990 industry codes on the horizontal axis. The upper left panel shows NAICS vs. IND1990 good job shares for all workers in 2000; the upper right panel repeats the plot for all workers in 2021. The lower left panel shows NAICS vs. IND1990 good job shares for workers with a BA degree in 2000; the lower right panel repeats the plot for workers without a BA degree in 2000. The reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ population ages 18-64 in 2000.

Figure A7: Census NAICS vs. CRY Estimated Industry Fixed Effects



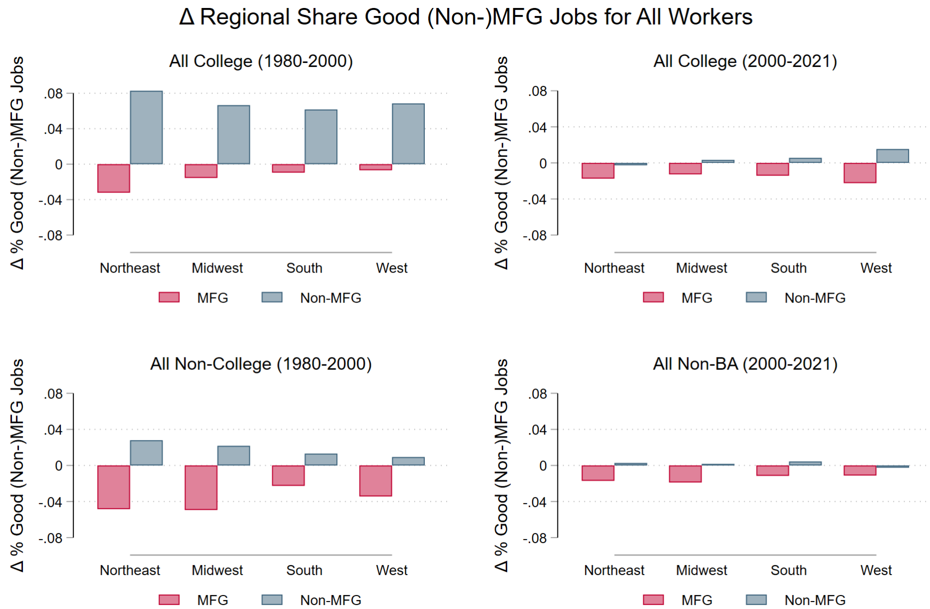
Notes: The figures plot the industry fixed effects we estimate using OLS Mincer wage regressions for Census NAICS industries in 2000 on the y-axis against those reported in Card et al. (2024) based on AKM regressions using LEHD data for 2008 to 2019 on the x-axis. To match CRY industries to ours, we use industry employment weights to aggregate the 311 CRY industries (based on four-digit NAICS codes) to our 206 Census NAICS codes. We then repeat the exercise for industry fixed effects we estimate at the three-digit NAICS level (89 industries). The left panel plots four-digit industry fixed effects (weighted z-scores) in the top row and the corresponding industry rankings in the bottom row; the right panel shows similar results for 3-digit industries. The reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by industry employment in 2000.

Figure A8: Employment in Good Job by Sector and Educational Attainment, 1980-2021



Notes: These figures show the distribution of employment across major sectors for our definition of good jobs (industries in the top tercile of estimated industry wage fixed effects for 2000) separately for workers with a BA degree in the top row and without a BA degree in the bottom row. The left panels show shares of national employment in good job industries accounted for by each sector; the right panels show the share of employment within each sector that is in good job industries. Sectors are based on IND1990 codes: Agriculture, Mining, Utilities, and Construction (10-60, 450-472); Manufacturing (100-392); Trade and Transportation (400-442, 500-691); Finance, Professional, Legal, and IT Services (700-721, 732, 841, 882-893); Health and Education Services (812-840, 842-881); Other Services (722-731); and Public Administration (900-932). Health, Education, and Public Administration are excluded as they have no top tercile industries.

Figure A9: Δ Share of Regional Employment in Good Job Industries, 1980-2000 and 2000-2021

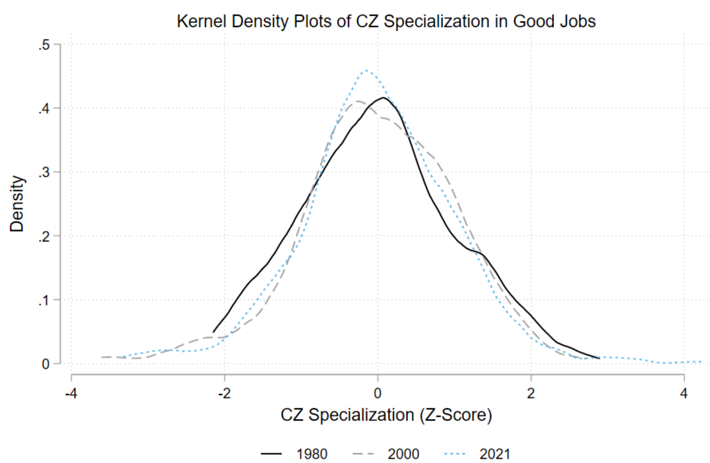


Notes: This figure shows changes in the share of regional employment in good job industries in manufacturing (in red) and in non-manufacturing (in blue) for 1980-2000 in the left panels and 2000-2021 in the right panels, with results for employment of workers with a BA degree in the first row and for employment of workers without a BA degree in the second row. The sum of the red and blue bars indicates the change in the share of overall regional employment in good job industries for a given time period and education group.

Figure A10: Kernel Density Estimates for CZ Log Good Job Shares: 1980-2021

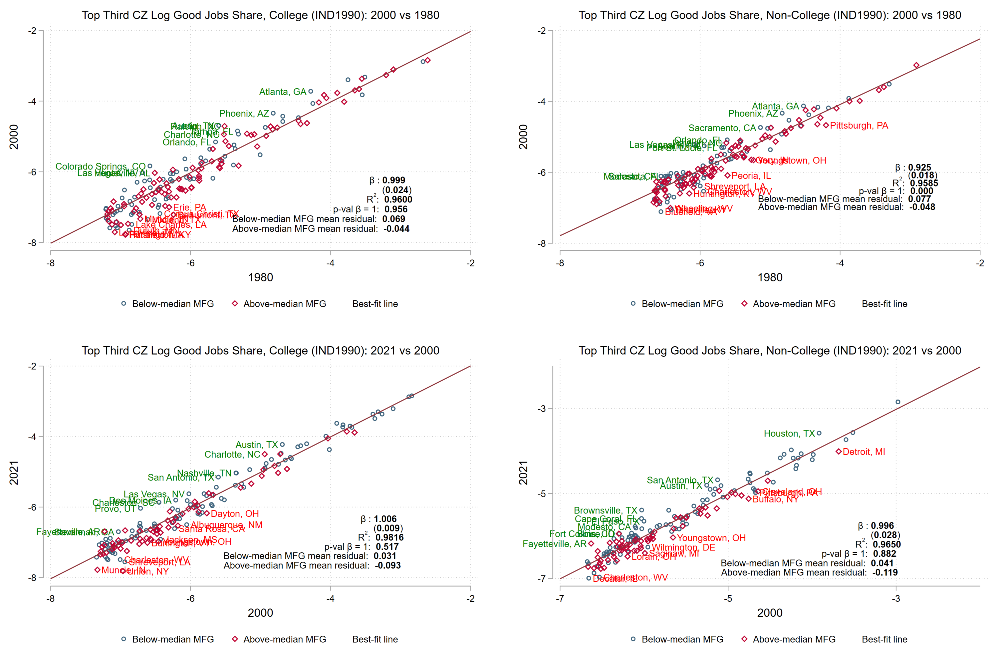
Notes: This figure plots kernel density estimates of z-scores for CZ log good job shares (CZ share of national employment in good job industries) by year for CZs in our sample (using good job definitions based on 2000).

Figure A11: Kernel Density Estimates for CZ Log Good Job Specialization: 1980-2021



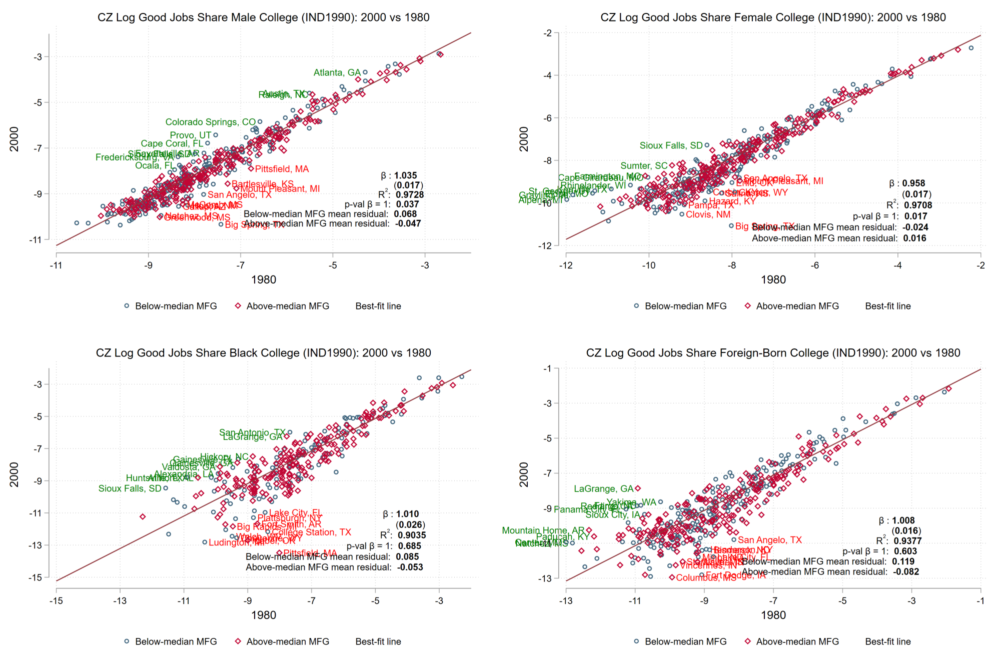
Notes: This figure plots kernel density estimates of z-scores for CZ log good job specialization (CZ share of national employment in good job industries/CZ share of national employment in all industries) by year for CZs in our sample (using good job definitions based on 2000).

Figure A12: Top Tercile Changes in CZ shares of Good Jobs by Education



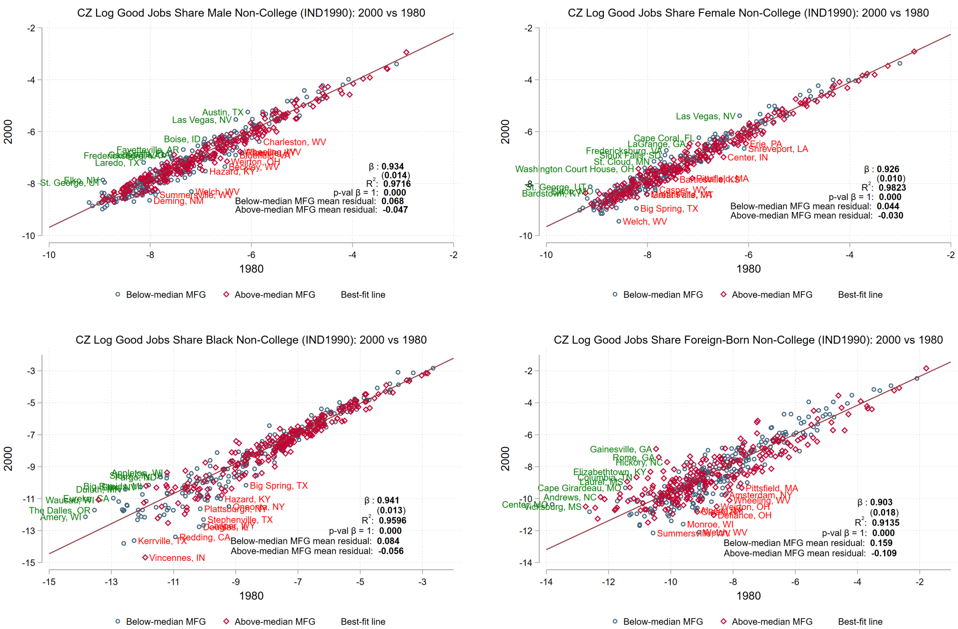
Notes: The graphs plot CZ log good job shares in 2000 on the y-axis against CZ log good job shares in 1980 on the axis, in the top row, and 2021 shares against 2000 shares, in the bottom row. Results for workers with a BA appear in the left panels and for those without a BA appear in the right panels. The sample is limited to CZs in the top tercile of employment in good job industries in the initial year. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure A13: Δ CZ shares of Good Jobs by Demographic Group, College: 1980-2000



Notes: The graphs plot CZ log good job shares in 2000 on the y-axis against CZ log good job shares in 1980 on the x-axis. The sample of workers is restricted to those with a BA degree and to males (upper left panel), females (upper right panel), Blacks (lower left panel), and the foreign-born (lower right panel). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure A14: Δ CZ Shares of Good Jobs by Demographic Group, Non-College: 1980-2000

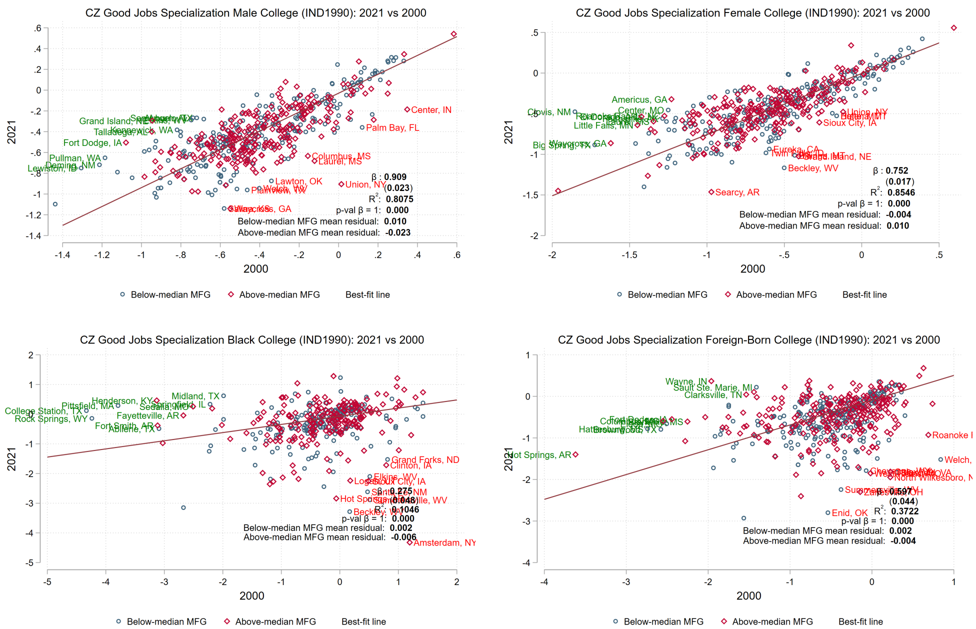


Notes: The graphs plot CZ log good job shares in 2000 on the y-axis against CZ log good job shares in 1980 on the x-axis. The sample of workers is restricted to those without a BA degree and to males (upper left panel), females (upper right panel), Blacks (lower left panel), and the foreign-born (lower right panel). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure A15: Δ Specialization in Good Jobs for Large CZs: 2000-2021

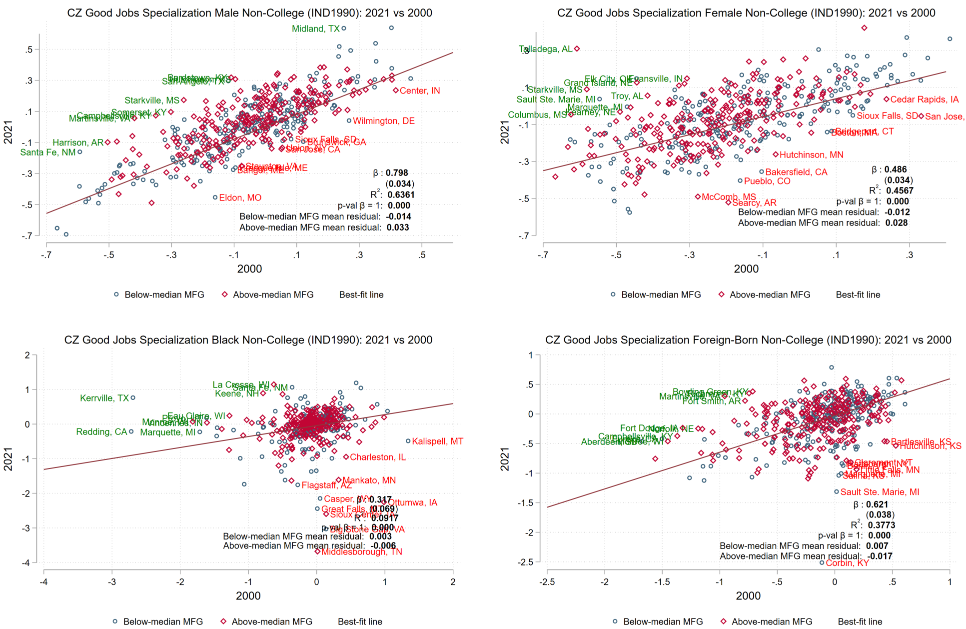
Notes: The graphs plot CZ log good job specialization in 2021 on the y-axis against CZ log good job specialization in 2000 on the x-axis. The sample is limited to CZs in the top tercile of good job specialization in 2000 in the top row and to CZs in the top decile of good job specialization in 2000 in the bottom row. Results for workers with a BA appear in the left panels and for those without a BA in the right panels. Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job shares are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure A16: Δ Specialization in Good Jobs by Demographic Group, College: 2000-2021



Notes: The graphs plot CZ log good job specialization in 2021 on the y-axis against CZ log good job specialization in 2000 on the x-axis. The sample of workers is restricted to those with a BA degree and to males (upper left panel), females (upper right panel), Blacks (lower left panel), and the foreign-born (lower right panel). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job specialization are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.

Figure A17: Δ Specialization in Good Jobs by Demographic Group, Non-College: 2000-2021



Notes: The graphs plot CZ log good job specialization in 2021 on the y-axis against CZ log good job specialization in 2000 on the x-axis. The sample of workers is restricted to those without a BA degree and to males (upper left panel), females (upper right panel), Blacks (lower left panel), and the foreign-born (lower right panel). Red (blue) dots are CZs with above-median (below-median) shares of employment in manufacturing in the base year. CZs with the 10 largest increases in good job specialization are named in green, and for the 10 largest decreases in red. Reported slope coefficients (and robust standard errors) are based on OLS regressions weighted by the CZ 18-64 population in the initial year.