

ORIGINAL ARTICLE

Open Access



The evolution of wage inequality within local U.S. labor markets

Anthony Eisenbarth^{1*†} and Zhuo Fu Chen^{2†}

Abstract

There are few concentrated studies on wage inequality across local labor markets at the city or metropolitan level. This paper studies the changes in wage inequality among 170 metropolitan areas by using micro-level data from the U.S. Census and American Community Survey from 1980 to 2019. We propose that shifts in the relative demand for “college-educated” or “college equivalent” workers have been persistent in both temporal and spatial dimensions; and that this persistence has contributed to the increase in wage inequality along with the rise in managerial employment. Using fixed-effects models, we find that on average, changes in managerial intensity between 1980 and 2019 accounts for 6.9% of the change in wage inequality across U.S. labor markets.

Keywords: Wage inequality, Labor markets, Labor demand

JEL Classification: B59, C33, J23, J31

1 Introduction

A voluminous literature on wage inequality (dispersion) documents the substantial widening of the U.S. wage structure that emerged during the 1980s, and which has ceaselessly grown in following decades in both the United States and globally (see Autor and Katz 1999; Acemoglu 2002b; and Piketty and Saez 2006). The surge in wage inequality is illustrated in Fig. 1 (plot a), which depicts a monotonic spreading out of the entire wage distribution for both men and women. The literature on wage inequality has explored how much of the growth in inequality can be explained by the erosion of labor institutions such as unions and the declining value of the minimum wage (for instance, Card 2001; Koeniger et al. 2007), with shifts in the relative demand for “skilled” labor in the form of college educated workers. Research has historically framed income inequality as a national issue, one best addressed through national policies that raise demand

for labor and redistribute resources. Widening disparities across and within places in the U.S., revealed in debates around wages, housing affordability, have motivated policymakers and researchers to give increased attention to the local dimensions of inequality.

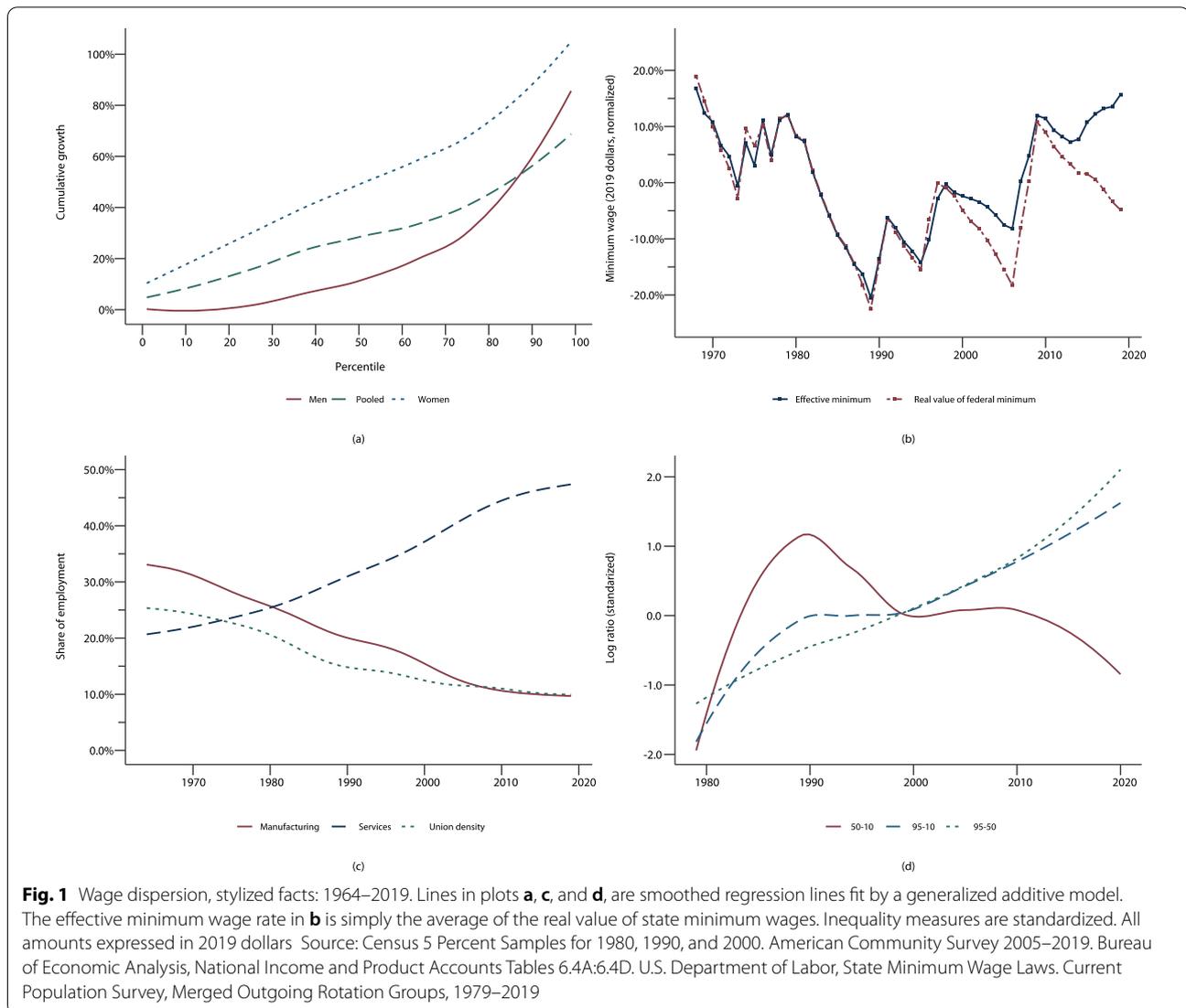
Nevertheless, aside from the large urban economics literature on the urban wage premium (see for instance, Gould 2007; Heuermann et al. 2010), there has been little concentrated study on the rise of wage or income inequality across local labor markets within the metropolitan or city level. Most studies on wage inequality, in fact, have been either at the national or state level (for example, Katz and Murphy 1992; Ciccone and Peri 2005). This may be due in part to the recognized fact that “within” or “between” group decompositions of the urban wage premium has been within, rather than among spatial units such as standard metropolitan statistical areas (MSAs). Baum-Snow and Pavan (2012), for instance, find that experience and wage-level effects are the most

*Correspondence: ageisenbarth@gmail.com

†Anthony Eisenbarth and Zhuo Fu Chen contributed equally to this work

¹ Department of Economics, University of Utah, 260 South Central Campus Drive, Gardner Commons Suite 4100, Salt Lake City, UT 84102, USA

Full list of author information is available at the end of the article



important “mechanisms” contributing to the urban wage premium.¹

Considerable attention has been given to fundamental changes in the institutions of the labor market, such as the decline in union membership and the falling value of the federal minimum wage (see for instance, Lee 1999; Autor et al. 2016; and Farber et al. 2020). Such trends are plotted in Fig. 1 (plots b and c). These figures show that the real value of the minimum wage, both at the federal and at the ‘effective’ level (the average of the state minimum rates) fell precipitously in the

1980s. At the same time, the decline in manufacturing employment increased its descent into the 1980s. Lastly, the widely used measures of wage inequality the $\log p(50)-p(10)$ or “lower tail,” $\log p(95)-p(50)$ or “upper tail,” and $\log p(95)-p(10)$ (the “overall” measure) ratios all increased dramatically in this period. But while the $p(95)-p(50)$ and $p(95)-p(10)$ measures have continued to increase, lower tail inequality has remained fairly constant since the end of the 1990s, and even recently, is beginning to decline.

Changes in trade terms through globalization also changed the composition of firms within the U.S. Manufacturing employment, for instance, has declined considerably over the past several decades, even as manufacturing output grew strongly. What had been a slow decline in employment accelerated after the turn

¹ Baum-Snow and Pavan (2012) find that these mechanisms are important for both high school and college graduates throughout the city size distribution. Differences in wage intercepts across location categories are more important for generating wage gaps between medium and small cities, while differences in returns to experience are more important for generating large-to-small city wage differentials.

of the century and especially during the Great Recession. Manufacturing employment bottomed in 2010, and overall employment in manufacturing is at its lowest levels since the U.S. entered the Second World War. The decline in manufacturing employment and union density coincided with the rising importance of the services industry, which grew from roughly 25% of national employment in the U.S. at the start of the 1960s to approximately half of total employment by 2010.²

These trends overlapped with the advent of the “Computer Revolution.” The vast improvements in information technology (IT) seemingly gave rise to a demand for a relatively more educated workforce with new and advanced technical skills. Growth in the college wage premium during the 1980s have been attributed to this correlation between the rise of IT and the growth in the relative wage for college educated workers. And hence, the effects derived from the computer and IT revolution have emerged as the leading hypothesis for explaining the growth in the relative demand for skills through the Skill Biased Technical Change (SBTC) argument. The SBTC contention, however, has its limitations. Perhaps the main difficulty, as both Card and DiNardo (2001) and Lemieux (2006), have argued, is that the relative demand for this “unobservable skill” of college educated workers should have been experienced in both the 1980s and 1990s; the fact that this occurred mostly in the 1980s is a stumbling block to the SBTC argument. In contrast, the college premium, the wage of college educated workers relative to high school workers, declined during the so-called “Roaring Nineties” rather than steadily increase as predicted by the core SBTC model developed by Katz and Murphy (1992).

An under-looked phenomenon in comparison, have been the fundamental changes in the relations between capital and labor during the 1980s, and perhaps more importantly in the workplace itself. On the one hand, new business practices and technologies have led many workers to supply their labor outside of the traditional employment relationship. An estimated 15 million American workers have “alternative arrangements” for their primary employment—a measure that includes independent contractors, on-call workers, temporary help agency workers, and workers provided by contract firms (Katz and Krueger 2019).

On the other hand, managerial and supervisory employment, as well as compensation, have grown steadily since the 1980s. Data from the Bureau of Labor Statistics’ *Occupational Employment and Wage Statistics* (OEWS) survey, which collects data on wage and salary workers in non-farm establishments provides information on compensation for managerial and non-managerial positions.³ In 1996, the average hourly wage for managerial and supervisory employees was \$30.13. By 2019, the average hourly wage for managerial and supervisory employees increased by 50%. In comparison, the real average hourly earnings of production and non-supervisory employees increased 30%, increasing from \$19.67 to \$23.51. Cumulatively from 1980, managerial compensation increased 48.1%, while regular workers experienced a 25.5% increase. The fact that managerial pay has grown far faster than the pay of regular workers indicates that managerial compensation growth does not simply reflect the increased value of highly paid professionals in a competitive race for skills.

In light of these stylized facts, we propose that while education attainment in the U.S. has increased relative gains for some in the labor force, domestic and global forces have led to an increase in wage inequality through the weakening of workers’ bargaining power and labor disciplining effect of firms leveraging more managerial and supervisory employees. Changes in the relative supply and demand for college educated workers cannot alone account for such broad sweeping changes in the wage structure. We note two trends: first, managerial employment has grown steadily throughout the past several decades, and secondly, managerial compensation has grown in real terms, whereas real compensation for regular (non-supervisory and non-managerial) workers have stagnated. This can be seen clearly in the rise of managerial and supervisory employees share of total compensation for the private sector, which rose despite the growth in managerial and supervisory employees.

We use U.S. Census and American Community Survey (ACS) data from 1980 to 2019, to explore and study the nature of changes in the education-specific employment shares and college wage premiums across 170 metropolitan areas.⁴ The principal approach follows the constant-elasticity-of-substitution (CES) methodology of Katz and Murphy (1992). The use of the CES method allows

² The Bureau of Economic Analysis industry groupings generally follow the North American Industry Classification System, better known as NAICS. The services industry is a general grouping of occupations and services for disparate industries such as hotel and lodging, legal services, and health care.

³ The OEWS data provides wage estimates for roughly 800 occupations and 415 industries. Prior to 1996, the OEWS program collected only occupational employment data for selected industries in each year of the three-year survey cycle and produced only industry-specific estimates of occupational employment. The 1996 survey round was the first year that the OEWS program began collecting occupational employment and wage data in every state.

⁴ Such an attempt is similar in nature to Black et al. (2009), Moretti (2013), and Lindley and Machin (2014).

us to estimate the elasticity of substitution between workers with diverse levels of education; in our case, the estimated slope of demand for more educated workers relative to less educated workers across metropolitan areas. The estimate can then be used to assess the extent to which changes in the college wage premium are due to a shift in relative demand.

Our instrumental variables analysis finds that the elasticity of substitution between college graduates and high school workers ranges from 2.11 for a pooled sample (both men and women), 1.65 for men, and 2.87 for women. These estimates are within the range obtained at the aggregate national level by Autor et al. (2008). For full-time, full-year (FTFY) workers, the estimates are 2.12, 1.60, and 3.26 for a pooled sample, men, and women respectively. We find that the implied elasticity of substitution is negatively related to metropolitan size, with smaller metropolitan areas having larger elasticities. With our estimates of implied demand, we document that demand for college graduates is negatively related to manufacturing employment as might be predicted by a model that is developed by Autor et al. (2003), lending some credence to the labor market “polarization” hypothesis. But we also show that implied demand for college graduates is strongly correlated with what Gordon (1990, 1994, 1996) referred to as “managerial intensity” or the ratio of managerial and supervisory employees to production employees.

With our elasticity estimates we construct a labor demand index for college graduates to explore how much the increase in the demand for skilled labor have led to an increase in wage inequality across metropolitan areas in the United States. Our results confirm at the metropolitan level Gordon’s thesis regarding the growth in managerial employment and its relation to wage inequality. We find that metropolitan areas with higher densities of managerial intensity experienced differential increases in wage inequality. On average, changes in managerial intensity between 1980 and 2019 account for 6.9% of the change in wage inequality as measured by the residual variance. Furthermore, managerial intensity is strongly correlated with implied demand shifts suggesting that a phenomenon of “reskilling” among managerial and supervisory employees with managerial employees earning college degrees. We offer an interpretation of our results that combines the empirical findings of the labor market polarization literature with the theoretical conceptions of labor process theory and Gordon’s labor control thesis. Our paper contributes to the growing literature that casts doubt on the contribution of technology to both the polarization process and increase in wage inequality (Beaudry et al. 2016; Salvatori 2018).

We begin in Section 2 by outlining the conceptual framework that motivates our empirical analysis. In

Section 3, we review the pertinent literature. Section 4 describes our empirical approach to estimating residual wage inequality and discusses the data. Section 5 gives our primary ordinary least squares (OLS) and two-stage least squares 2SLS estimates utilizing the Katz-Murphy model that we use to interpret relative wage data and evaluates the ability of simple demand shift stories to explain the observed patterns of changes in relative factor prices and supplies at the metropolitan level. Section 6 incorporates the elasticity estimates derived from the 2SLS estimation as well as estimated wage percentiles, to study the impact that the increase in demand for skilled labor have on the wage structure in metropolitan areas. And finally, Section 7 provides a conclusion of our findings.

2 Differences across metropolitan areas

Specifically, metropolitan areas are defined by the U.S. Office of Management and Budget (OMB) as an urbanized area with at least a minimum population of 50,000 inhabitants within one or more counties. Through the use of these large areas, we are provided with large populations to draw upon to mitigate measurement issues that arise with the use of observational data, specifically in our case coverage error.

Table 1 reports the characteristics of metropolitan areas with the highest concentration of college graduates in the 25-to-65-year-old workforce and compares them against those with the lowest proportion of college graduates. In 1980, the start of our considered time period, the MSA with the highest college population in its workforce was Ann Arbor, Michigan, which had a college population of 38.3%. Ann Arbor, Michigan is approximately three times larger than the MSA with the lowest college population, Ocala, Florida, which had a college population share of 9.9%.⁵

A standard variance decomposition is a common approach to assessing the quantitative contributions of observable and unobservable components of wage dispersion to changes in overall wage inequality. This approach starts with a standard wage equation,

$$W_{it} = \mathbf{X}_{it}\beta_t + \varphi_{it}, \quad (1)$$

where W_{it} is the log wage of individual i in year t , \mathbf{X}_{it} is a vector of observed individual characteristics (e.g., experience and education), β_t is the vector of estimated returns to observable characteristics in t , and φ_{it} is the log wage residual (which depends on the prices and quantities of unobserved skills, measurement error, and estimation error). The orthogonality of the predicted values and the

⁵ These estimates are for full-time, full-year workers, not currently enrolled in school, between the ages of 25 and 65 years old.

Table 1 MSAs with the largest and smallest shares of college graduates. Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

	Level in 1980			Change from 1980 to 2019		
	College population	College premium	Wage inequality	Change in college population	Change in college premium	Change in wage inequality
<i>MSAs with the largest college population in 1980</i>						
Ann Arbor, MI	38.3	28.6	36.1	15.5	24.8	14.6
Washington D.C.	35.3	49.4	40.4	15.4	17.2	14.6
Champaign-Urbana-Rantoul, IL	31.6	28.9	36.2	14	16.5	6.6
Austin, TX	30.8	44.3	36.4	10.9	34.2	16.2
Gainesville, FL	30.3	44.1	35.8	12.3	12.8	11.6
Fort Collins-Loveland, CO	29.8	35.0	37.9	15.4	22.5	8.8
Raleigh-Durham, NC	28.5	42.7	33.5	15.4	19.1	17.9
Denver-Boulder, CO	28.2	41.7	38.9	13.9	17.7	11.2
San Jose, CA	28.2	47.9	38.6	21.3	31	25
San Francisco-Oakland-Vallejo, CA	27.5	36.7	40.2	18.1	10	18.6
<i>MSAs with the smallest college population in 1980</i>						
Ocala, FL	9.9	38.1	38.6	7	46.3	3.2
Brownsville-Harlingen-San Benito, TX	10.4	44.3	38.3	6.8	24.8	8.2
Visalia-Tulare-Porterville, CA	10.9	48.4	41.2	2.9	20.8	4.5
Saginaw-Bay City-Midland, MI	11.1	28.8	35.7	10.8	28.5	4.3
Scranton-Wilkes-Barre, PA	11.3	40.3	30.8	15.5	25.5	5.3
Youngstown-Warren, OH	11.4	27.8	36.6	10.6	21.4	0.9
Joplin, MO	11.4	39.7	33.6	10.3	29.3	4.7
McAllen-Edinburg-Pharr-Mission, TX	11.8	46.3	42.1	6.1	24.8	3.0
Yakima, WA	12.2	30.4	41.5	2.7	42.8	-2.0
Lakeland-Winterhaven, FL	12.6	44.9	37.7	3.8	43.2	-0.2

The college population share is defined as the share of the total working population not enrolled in school between the ages of 25 and 65 years old, who have a college degree or more. The change in the college population is the change in the working population share of college graduates between 1980 and 2019. The change in wage inequality is the change in wage inequality between 1980 and 2019 measured as the variance of log real weekly earnings of all workers 18 to 65 years old. All rates are multiplied by 100

residuals in an Ordinary Least Squares (OLS) regression implies the variance of W_{it} can be written as,

$$\text{Var}(W_{it}) = \text{Var}(X_{it}\beta_t) + \text{Var}(\varphi_{it}) \quad (2)$$

The variance of log wages can be decomposed into two components: a component measuring the contribution of observable prices and quantities and the residual variance (a component measuring the effect of unobservables). The first component $\text{Var}(X_{it}\beta_t)$, is often referred to between-group inequality, and the second, $\text{Var}(\varphi_{it})$ the residual variance, is referred to as within-group inequality. We extend this approach to the metropolitan areas in our sample, focusing on the residual variance.⁶

⁶ A shortcoming of a reliance only on this approach is that the variance may not be the only inequality measure of interest especially given the sensitivity of the variance to changes in the tails of the distribution. For this reason, other measures such as the standard deviation and the $\log p(90)-p(10)$ wage differential are sometimes used. A disadvantage of moving away from the variance and examining other measures of inequality, such as quantile measures like the $\log p(90)-p(10)$ differential, is that these alternative measures typically do not uniquely decompose into between and within components.

Metropolitan areas in the top panel (those with high shares of college graduates) of Table 1, tended to have larger increases in wage dispersion than those in the bottom panel. This assessment is summarized in Fig. 2 (plot a) where the college employment share in 1980 is on the x -axis and the change in the residual variance from 1980 and 2019 is plotted on the y -axis. Likewise, plot b of Fig. 2 depicts an increasing concentration of college graduates in metropolitan areas with prior higher shares of college graduates. In the plots, the size of the bubbles reflects the metropolitan area's population in 1980, which further shows (plot b of Fig. 2) that college graduates tend to locate themselves in larger metropolitan areas. These spatial patterns have been noted by Moretti (2013), among others.

Summarized estimates for the variance and residual variance of log hourly wages are reported in Table 2, which also provides summary statistics on the average employment share of college educated workers as

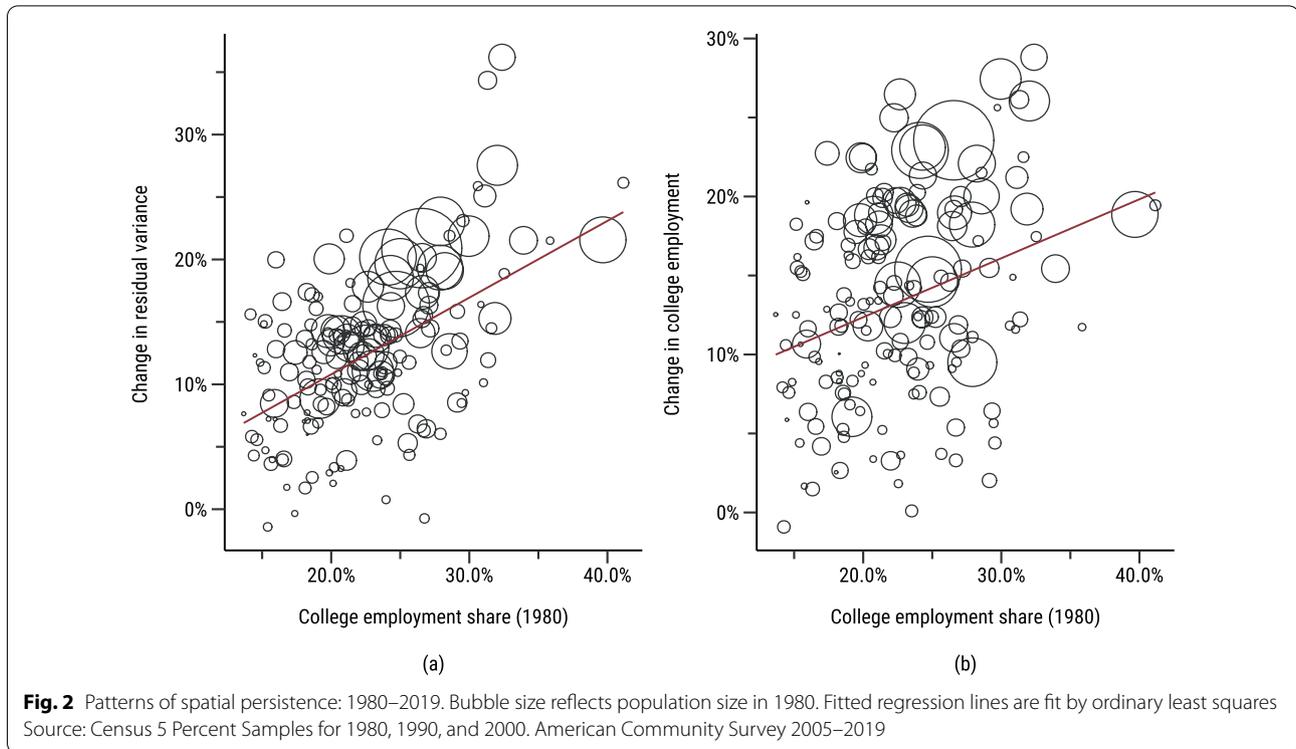


Table 2 Wage dispersion, Summary statistics. Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

	College premium	Managerial intensity	Employment share	Variance	Residual variance
1980	41.2 (8.0)	17.6 (1.45)	22.0 (4.65)	39.1 (3.81)	21.9 (3.27)
1990	56.1 (7.0)	19.4 (1.65)	26.0 (5.83)	39.1 (3.21)	20.6 (2.18)
2000	62.3 (9.00)	20.0 (1.91)	29.0 (7.19)	42.3 (4.67)	24.7 (2.92)
2010	62.1 (8.0)	20.1 (1.88)	32.0 (7.51)	50.3 (5.72)	27.0 (3.48)
2019	63.2 (10.0)	20.8 (2.09)	34.0 (8.76)	55.3 (7.06)	29.7 (3.85)

This table shows summary statistics for the MSAs in our sample regarding college educated employment. The employment share of college educated workers is similarly defined for employment: it is the ratio of all 18 to 65 years old college educated workers to all currently employed persons between 18 and 65 years old. Managerial intensity is the ratio of managerial and supervisory employees to non-supervisory employees for the private, non-farm sector. The delineation of managerial and supervisory employees were established through Census occupation codes. Lastly, the college premium is the relative real hourly wage of college educated workers to non-college educated workers. Standard deviations reported below in parentheses. All rates are multiplied by 100

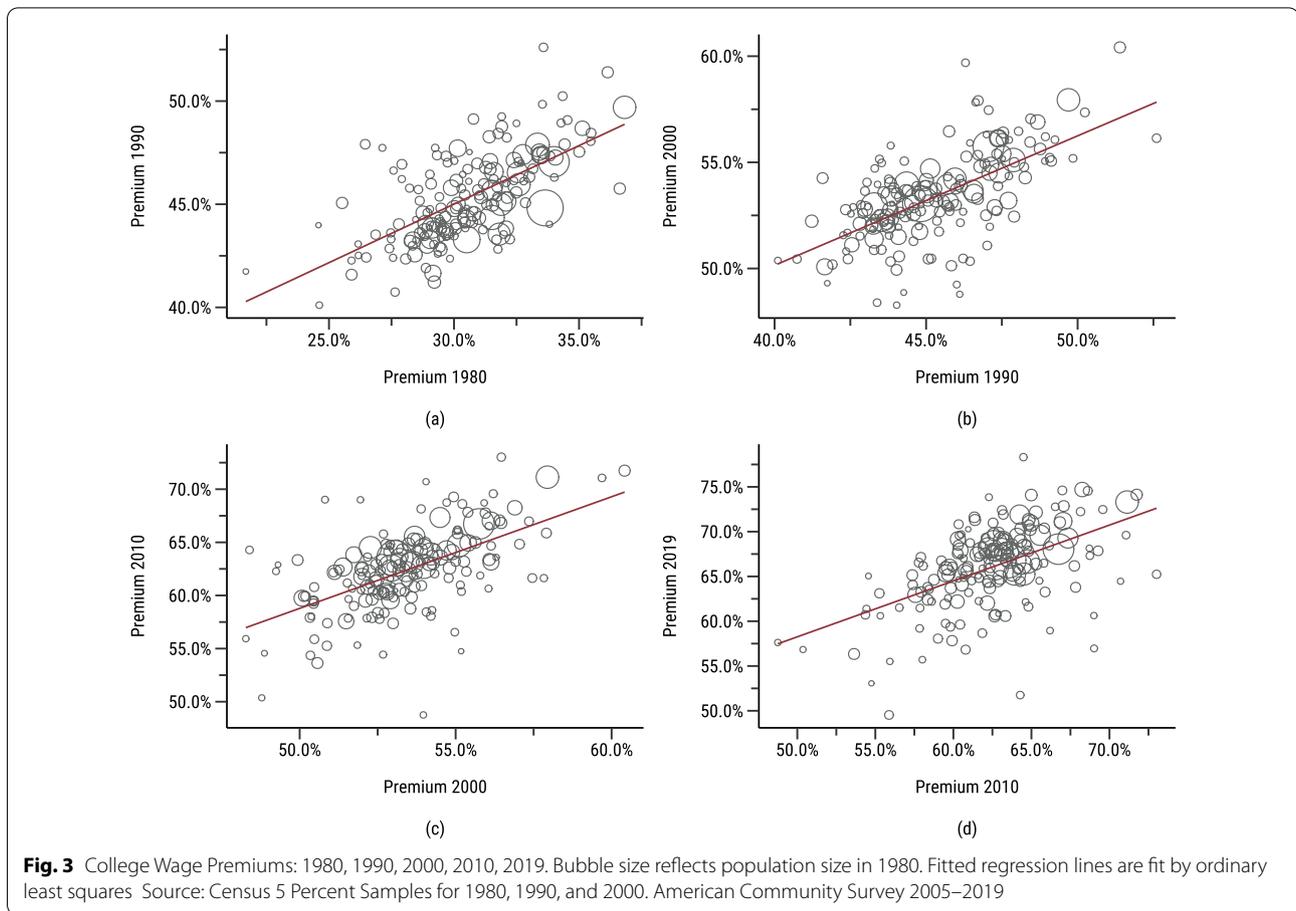
a share of total employment for all workers within the sampled MSAs. It also provides information on the average employment of college graduates within the sampled MSAs. The increasing trend in the college wage premium

goes hand in hand with the increasing concentration of college graduates within larger metropolitan areas, as seen in Table 1.

Although all MSAs experienced increases in the college wage premium, some MSAs experienced considerably less growth in the college wage premium and change in hour shares of college graduates. Among these Augusta, Daytona, El Paso, Elkhart, Gulfport, Hartford, Lafayette, and Monroe experienced growth in the college wage premium below 5% from 1980 to 2019; this was well below the average increase of 20% (Table 1). Figures 2 and 3 reveal both a high degree of persistence and an increase in the relative demand for college educated workers.

And yet these patterns vary across metropolitan areas as evidenced by the increase in the standard deviations (Table 2). The same holds for the college wage premium. Black et al. (2009) note that, at a point in time, there are substantial spatial differences in the college wage premium: in their specific case, cross-sections of 1980, 1990, and 2000 census years. We find similar results.

Different forces may be responsible for the increase in relative demand of skilled workers, especially the transformation of the economy brought on by the computer revolution of the 1980s (Krueger 1993). Another possible explanation for the increase in the relative demand for skilled workers is a positive shock to the product demand



faced by industries that employ relatively more skilled workers and are agglomerated in certain cities. For example, the demand for financial services have increased significantly within the last several decades (Beaudry et al. 2010). By the same token, it is more than reasonable to infer that wage inequality has increased in cities where specific industries no longer have the presence they once did: several studies have explored this aspect, for example, Leonardi (2015) and Baum-Snow et al. (2018).

Skilled workers, alternatively, may move to certain cities because the relative supply of skilled labor increases in those cities, as skilled workers are enticed by local amenities. One can assume that amenities are fixed, but the taste for those amenities may increase (Diamond 2016), or both amenities and tastes can be fixed. Amenities, however, are considered normal goods, so that college graduates are more likely to consume more of it relative to high school graduates (Gyourko et al. 2013).

One of the most prevalent narratives in the academic literature posits that in the past 40 years, technological advancement and the increase in educational attainment brought about changes in the relative demand and supply

in the United States and beyond. But the development has not been steady. From the end of World War II to the late 1970s, the relative supply of college workers rose robustly and steadily, with each cohort of workers entering the labor market boasting a proportionately higher rate of college education than the cohorts immediately preceding (Goldin and Katz 2007).

Reversing this pattern, the rate of growth of college workers declined in the early 1980s, with the falling relative supply of college graduates (skilled workers) and the adoption and development of new technologies; the conditions were favorable for returns to skill (the college premium) to increase (Acemoglu and Autor 2011). The core of the argument is traced to Tinbergen (1974) idea that new technologies require more skilled workers and hence, the introduction of new technology leads to a continual demand for more skills.

Moreover, college-educated laborers often seek out employment that is clerical, administrative, or technical, hoping to employ the skills they have acquired from their university training. Globalization has been an ongoing process for the past two decades. As manufacturing

jobs are off-shored to developing countries with relaxed labor laws, manufacturing employment in formerly vibrant industrial metropolitan areas is in decline. The inter-competition between U.S. laborers with foreign laborers has allowed the global firms to create disincentives to organize and form labor unions (Bivens 2013). As labor unions become scarce in the U.S., the influence of unions as a political vehicle for collective bargaining has deteriorated due to the competitive dynamics of global capitalism.

2.1 Theoretical context

An extensive literature contends that the pronounced rise in wage inequality in the United States and other advanced nations commencing in the 1980s results from Skill Biased Technological Change (SBTC). The theoretical cornerstone of this literature is what Acemoglu and Autor (2011) refer to as the “canonical model,” which features two distinct skill groups—most often, college and high school workers—performing two distinct and imperfectly substitutable occupations or producing two imperfectly substitutable goods.⁷ Conceptually simple, the canonical model has been the workhorse model for many empirical studies and assumes that technology is factor-augmenting, complementing either high or low-skill workers.

Following studies brought forward limitations to the SBTC contention. Autor et al. (2008) looked at changes in the distribution of wages and concluded that increasing employment in higher-skill jobs and decreasing employment in lower-skill jobs in the 1980s explain rising wages in the former and falling wages in the latter. But in the 1990s, employment in low-skill jobs also increased. Acemoglu and Autor (2011) updated these analyses to the present and found that the college wage premium remained relatively steady in the 2000s despite a slowdown in the relative supply of college graduates compared to high school graduates. They infer that the increase in the relative demand for college graduates therefore also slowed down.

Several of the studies stressing the limitations of the SBTC narrative proposed a new hypothesis, blending together the results of Autor et al. (2003), Goos and Manning (2007), and Autor et al. (2008), which contends that the years following the 1980s have witnessed a substantial

growth in the demand for occupations involving “cognitive” tasks and a reduction in the demand for more middle-wage routine occupations. The Routine Biased Technological Change (RBTC) hypothesis claims that growth in employment in both the highest-skilled (professional and managerial) and lowest-skilled (personal services) occupations, with declining employment in the middle of the distribution (manufacturing and routine office jobs), make a process of what Goos and Manning (2007) call “polarization.”

The central idea of the RBTC is that technological improvements, whether through the adoption of machine learning, robotics, automation, have made it possible to replace workers performing routine tasks by machines. The substitution or displacement of workers is driven by the declining price of computer capital. Importantly, the labor-capital substitution in favor of computer or technological capital reduces the relative demand of labor in middle-wage occupations due to the increasing ability of machines to perform routine tasks, which characterize these occupations (Acemoglu 2002a; Autor and Dorn 2013).

Technology, of course, is only one factor that can affect the demand for college workers; others include international trade, outsourcing, and consumer demand patterns. The notion that technology is a relentless force creating demand for higher skills is contradicted by research in other fields. A dominant view of technology, in sociology, for instance, is that technology is often designed precisely to reduce skill requirements rather than the reverse. The technology associated with scientific management, such as assembly lines, reduces average skill requirements, increases the supply of labor that could perform most jobs, and lowers wages in the process. Technological adoption also reduced the control and discretionary effort that workers could exercise in those jobs (Braverman 1974). Additional studies have also strongly suggested that employer choices determine whether skill requirements rise or fall for different workers (Zicklin 1987).

Indeed, a growing body of literature has come to cast doubt on the extent of technology as the primary driver of labor polarization. Beaudry et al. (2014) argue that the demand for higher-skill jobs that require college degrees is actually declining and that college graduates are forced to look to jobs that require less skill. Subsequently, they displace applicants without a college degree, who then fare worse than before. In an extension of their work, Beaudry et al. (2016) contend that the IT revolution and its “de-skilling” process can be seen as a “General Purpose Technology,” which will eventually reach maturity if it has not already. They propose that this maturation process has been coming into effect since 2000. In a similar

⁷ Influential studies papers by Bound and Johnson (1992), Katz and Murphy (1992), and Juhn et al. (1993) argued that the surge of inequality in the 1980s reflected an ongoing, secular rise in the demand for skill that accelerated during the 1980s with the introduction of personal computers and advances in information technology (Krueger 1993). The model proposed by Katz and Murphy (1992) is held by Acemoglu and Autor (2011) to be the canonical model. See Autor and Katz (1999) for an exhaustive review of the early literature and Acemoglu and Autor (2011) for a more recent evaluation.

vein, Salvatori (2018) finds that the increase in the educational attainment of the workforce is likely to have contributed significantly to the most prominent feature of the polarization process in the U.K.

While technological change and its effects on the skill requirements has been much explored in the literature, a relatively unexplored dimension has been capital-labor relations. Monumental changes occurred in the 1980s, with firms more intensely discouraging organized labor and collective bargain agreements (see for instance, Freeman and Kleiner 1990; Bronfenbrenner 2000). Subsequently, labor unions have become less influential in the collective bargaining process in the U.S (Farber et al. 2020). The 1980s also saw a revolution in corporate governance and management ideology popularly termed the “Shareholder Revolution.” While popular business views espoused downsizing, rather than reducing total labor costs as a share of business income (i.e., redirecting corporate income from workers and managers to shareholders), the primary effect of prototypical shareholder value strategies was to transfer labor income from production workers to managers (Goldstein 2012).

Working within the context of the so-called labor discipline or Bowles-Gintis model of the efficiency wage model,⁸ Gordon (1990, 1994, 1996) first proposed that patterns in wage inequality could be explained through the combination of factors relating to the regulation of worker effort in the United States. Referencing the great institutional changes in the labor market that took place in the 1980s, Gordon (1996) suggests that theories such as the skills mismatch, SBTC, and labor market polarization theories for rising wage inequality in the U.S. are unpersuasive.

Gordon highlights two trends that occurred in the 1980s: (1) the stagnant growth in real wages and (2) an increasing number of managerial and supervisory employees who experienced increases in their earnings. Gordon (1996) suggests the two are related, arguing that stagnant real wages create a need for more intensive managerial supervision to ensure that workers are properly monitored and carry out assigned tasks. These managers and supervisors are then differentially compensated based on their seniority, relative position in the production process, and complexity of the labor tasks they oversee.

⁸ The “shirking” model of the efficiency wage paradigm most often refers to the model presented by Shapiro and Stiglitz (1984) and is often referred to as the Shapiro–Stiglitz model whereas the “labor discipline” or “labor extraction” model is that presented by Bowles (1985). It is perhaps more accurate to refer to the model developed by Bowles as the Bowles–Gintis model, for many of the precepts of Bowles’ model are developed by Gintis (1976) and further refined by Bowles and Gintis (1977). For a detailed review of the efficiency wage literature consult Katz (1986) or Akerlof and Yellen (1987).

While a full recapitulation is unnecessary, a review of the Bowles–Gintis model’s main elements is fruitful to elucidate this argument. In the Bowles–Gintis model, supervisory inputs are necessary to monitor both the intensity of labor services provided by production workers and the effectiveness of monitoring activities by their immediate supervisor. Wage incentives elicit labor effort only if complemented by supervision; if workers are not observed in their work, given conflicts of interest between employers and production employees, they would have no incentive to increase their labor effort even in return for a higher wage.⁹ In its simplest formulations, labor effort e is a function of an efficiency wage w^* (the cost of job loss) and some level of supervision s ,

$$e = \iota(w^*, s), \quad \frac{\partial \iota}{\partial w^*} > 0, \quad \frac{\partial \iota}{\partial s} > 0 \quad (3)$$

By assumption the only input into supervision is supervisory labor, and hence cost minimization (profit maximization) by the ideal firm involves choosing the wage w^* and level of supervision s that minimize the cost of a unit of labor input l . The firm chooses the optimal intensity of supervision which satisfies the first-order conditions $l_s^*/l_w^* = \xi$, where ξ is the hourly cost of a supervisory input or the supervisory wage (see Bowles 1985 for the full derivation).

The extraction of work effort is considered to be separable from the rest of the production process. In this case, firms set wages to minimize the ratio of hourly labor costs to hourly work effort. The equilibrium wage generated by effort-regulation models will generally exceed the market-clearing wage; equilibrium will therefore be characterized by persistent, involuntary unemployment, which serves as an additional regulating device for workers.

A functional expression for the determinants of supervisory intensity is

$$s = s(w^*, \xi, \mathbf{Z}), \quad (4)$$

where \mathbf{Z} is a vector of other factors affecting the labor effort function. It is easy to see that in the event of a fall in the cost of job loss, corporations and firms hire more managerial and supervisory employees to compensate for the decline in the cost of job loss.

Other factors, however, may play an important factor in determining the level of effort workers provide and empirical studies have utilized union density, job finding

⁹ The relationship between the worker and the firm is conceptualized as a classic principle-agent problem. Employers and workers have a conflict of interest in the production process in the specific sense that the employer’s interests (as measured by profits) are enhanced by being able to compel the worker to act in the interest of the employer.

probability, the unemployment rate, quit rate, and occupational complexity as mitigating factors (see for example, Rebitzer 1987; Gordon 1990; Green and Weisskopf 1990; Green and McIntosh 1998; Fallick et al. 2006).

3 Literature

Several influential papers by Bound and Johnson (1992), Katz and Murphy (1992), and Juhn et al. (1993) argued that the surge of inequality in the 1980s reflected an ongoing, secular rise in the demand for skill that commenced decades earlier and accelerated during the 1980s with the introduction of personal computers and advances in information technology (see Krueger 1993; Beaudry et al. 2010). When this secular demand shift met with an abrupt slowdown in the growth of the relative supply of college-equivalent workers during the 1980s—itsself a consequence of slowing educational attainment for cohorts born after 1949 and of smaller entering labor force cohorts—wage differentials expanded rapidly (see Autor et al. 1998; Card and DiNardo 2001; Goldin and Katz 2007). The relative supply of college graduates then continued to rise without the college premium declining as a result; this was taken as evidence of a shift in technology biasing demand toward more skilled or educated workers. Together, these papers encapsulate the core of the Skill Biased Technological Change (SBTC) argument established early in the literature.¹⁰

Autor et al. (2003), Goos and Manning (2007), Autor et al. (2008), and Autor and Dorn (2013) contend that the years following the 1980s have witnessed a substantial growth in the demand for occupations involving “cognitive” tasks and a reduction in the demand for more middle-wage routine occupations. The Routine Biased Technological Change (RBTC) hypothesis claims that growth in employment in both the highest-skilled (professional and managerial) and lowest-skilled (personal services) occupations, with declining employment in the middle of the distribution (manufacturing and routine office jobs), entail a process of “polarization” into which the labor force is bifurcated into low and high-skill occupations.

From the five set of tasks originally set forth by Autor et al. (2003), the RBTC hypothesis divides workers into three categories; (1) high-skill or what the literature

terms “cognitive” or “abstract” occupations who consist mainly of managers, professionals, and technical workers and are seen as complementary to information technology (IT) capital and the organizational forms that go with it; (2) middle-skill or “routine” task occupations, which are mainly done by production and clerical workers, who are seen as easily replaced by the new technology; and (3) low-skill or “manual” task occupations, which are laborer and service type occupations, which, although they do require low-skill, are not easily substituted for with IT capital (Acemoglu and Autor 2011).¹¹

While the RBTC hypothesis, introduced by Autor et al. (2003), has replaced SBTC as the most conventional approach to explain changes in the labor market structure induced by technological change, unresolved issues persist. Empirical work, particularly, has been limited in its ability to dissect the distinction between skills in its classification methodology. For example, what constitutes a “cognitive” or “abstract” task is neither clearly nor consistently defined. The definition of “routine” tasks is also problematic. Driving an automobile is widely considered a non-routine task. Although it involves repetition of core elements and might be considered monotonous (routine from the worker’s perspective), it also requires the use of skills that human beings have a comparative advantage when compared with technology.

Perhaps the major drawback of the RBTC approach is the lack of a unified scheme for data analysis, which has authors using different data sources and classifying tasks based on the information available in the survey they use. This creates additional difficulties when interpreting and comparing the results across studies. For example, “managerial tasks” are included in the abstract or cognitive category. While it seems reasonable to assume that cognitive effort is required to perform managerial tasks, the precise identification of what are managerial tasks in each time and place depends on the social organization of work. The same can be said about “quality control” as an indicator of routine work and tasks. Quality control might be routine and repetitive in traditional production line jobs that involve mostly manual work and basic tasks with machines, but not necessarily in other activities.

Autor (2013) suggests that future research can benefit from using a task-based approach to further investigate the job polarization trends in industrialized economies

¹⁰ Technology is neither specified nor measured directly in typical SBTC studies, rather it is assumed to be an attribute of the economy that is ever increasing and often proxied by a simple time trend. Computer use or adoption is a favorite illustration of such technology (see for instance, Krueger 1993; Autor et al. 1998). Autor et al. (2003) look directly at the effect of computer use on skill requirements and found that it increased higher-skill, non-routine tasks while reducing lower-skill, routine tasks, also consistent with a SBTC view.

¹¹ A conventional approach is to “merge” job task requirements from the Fourth Edition of the US Department of Labor’s *Dictionary of Occupational Titles* (DOT) first published in 1977 and its 1991 Revised Edition to existing Census occupation classifications to measure routine, abstract, and manual task content by occupation. The reliance on the 1977 DOT job requirements is questionable especially given the 50 year span since its publication.

and how to resolve measurement errors.¹² Expanding on Autor's task-based approach, Salvatori (2018) finds that the sizable increase in university graduates in the U.K. is the main contributing factor in the "polarization" over the last three decades rather than technology, a finding consistent with Beaudry et al. (2016).¹³

Several studies have addressed the question as to whether skill requirements at the workplace have been increasing and if these changes are associated with technological change (for instance, Howell and Wolff 1992; Autor et al. 2003; and Autor and Dorn 2013). The literature recognizes that there are a variety of measures to categorize skill levels across different industries as opposed to the single measure based on education attainment for workers. Howell and Wolff (1991) and Howell and Wolff (1992) contend increases in skill requirements appears to be inversely related to the growing rate of investment in information technologies; they find their results linked to the deskilling of production workers and to the growing shares of managerial and supervisory employees.¹⁴ Autor and Dorn (2013) offer a unified analysis of growth in low-skill service occupations between 1980 and 2005 using Census data. Their results are generally supportive of the "routinization" hypothesis (put forward by Autor et al. (2003)), which suggests that the effect of technological progress is to replace "routine" labor of clerical and craft jobs in the middle of the wage distribution.

A relatively unaddressed question has been the role of heterogeneity for both firms and workers across spatial dimensions.¹⁵ Moretti (2013) and Lindley and Machin (2014) are among the few studies on spatial differences

in labor market wage inequality in the United States. Moretti finds that changes in real wage inequality between college-educated workers and non-college educated workers have grown less in real terms than it has in nominal terms; but more importantly, Moretti finds that increased housing costs for college-educated workers relative to less skilled offsets gains in utility from the increase college wage premium between 1980 and 2000. Lindley and Machin, studying both MSAs and states between 1980 and 2010, find that MSAs and states that experienced greater growth in computer use and research and development (R&D) intensity—measured as the share of state gross domestic product—also experienced greater increases in the relative demand for college-educated workers.

In the second part of the regression analysis, we study how changes in the industry mix of metropolitan areas affect the local wage structure via the increase in the log variance of real hourly wages. The most common approach in the literature is to include variables measuring overall employment or unemployment rates and the share of employment in various industries, particularly manufacturing (durable and non-durable goods separately), in an equation exploring the determinants of area wage or income inequality. This is the approach done by Karoly and Klerman (1994), who examine wage inequality in groups of states between 1973 and 1988. They find that the variance of log wages was lower in states with a larger fraction of employment in manufacturing, although the result was not robust for the inclusion of state fixed-effects. Cloutier (1997) adopts a similar approach in examining family income inequality in metropolitan areas in 1979 and 1989; she finds evidence of lower levels of inequality in areas with higher shares of manufacturing employment.

Black et al. (2014) provide a detailed evaluation of wage inequality across 21 metropolitan areas in the U.S. for college graduates relative to high school graduates of similar age groups. Their results, however, are confined to a narrow range (21) of MSAs and a sample of workers (white-non-Hispanic males). Diamond (2016) uses a static discrete choice model allowing for workers to have heterogeneous preferences for cities. She provides empirical evidence that college and high school graduates between 1980–2000 increasingly choose to live in different cities because of endogenous amenities within high-skilled cities. Changes in rent, wages, and local amenities further exacerbate wage differences between college graduates versus high school

¹² The task based approach suggests using three feasible methods to address the measurement problem: (1) "use occupations as proxies for job tasks" by aggregating many exhaustive occupations into a few broad categories, such as production or managerial, as most occupation schemes are hierarchical by design; (2) employing a "task categorization step" to reduce the role of sub-jectivity with descriptors obtained in the DOT and *Occupational Information Network* (O*NET); and (3) directly "collect job task information directly from survey respondents alongside other demographic, employment, and wage data" (Autor 2013)

¹³ Salvatori (2018) uses datasets from the U.K. Data Archive (NESPD) consisting of the Labour Force Survey (LFS), New Earnings Survey (NES, 1979–2002), Annual Survey of Hours and Earnings (ASHE) to investigate the U.K. labor composition changes for the 1979–2012 period. Salvatori (2018) updates Goos and Manning (2007) with a longer period and incorporates Autor's task-based approach to account for measurement problems.

¹⁴ Howell and Wolff (1991) use direct measures of job-skill requirements from the U.S. Department of Labor's *Dictionary of Occupational Titles* (DOT) to examine the effects of changing occupational and industry employment patterns on the skill composition. While they find an increase in the demand for cognitive skills, they also find a substantial slowdown in the rates of growth of those skills. Howell and Wolff (1992) suggest that structural differences in production during the 1960s–1980s resulted in firms increasing their demand for cognitive skills during this transition period. But more importantly, they also find that the growth in the skill measures do not appear to be continuous; there is little correlation between skill growth in the 1960s and skill growth since 1970.

¹⁵ The role of heterogeneity has also been explored by Card et al. (2013) who find that changes in occupation content from 1985 to 2009 in West Germany and increasing heterogeneity between workers generated a rise in wage inequality.

graduates in cities spanning three decades. Like Diamond, Farrokhi and Jinkins (2019) use a discrete choice model to put forward evidence that there is a relationship between city size and wage inequality across U.S. cities. They show that 16.5% of the observed variation in skill wage premium is a result of the cities' geographic location, although their estimates are confined to the 2000 Census year.

Hershbein and Kahn (2018) adopt the RBTC approach to a panel of 381 metropolitan areas from 2005 to 2015 to test whether skill requirements increased in the aftermath of the Great Recession. Using online job posting data collected by Burning Glass Technologies, they adopt the methodology of Acemoglu and Autor (2011) to distinguish "routine-cognitive" occupations from "routine-manual." They find that the skill requirements of jobs via job ads increased in MSAs that suffered larger employment shocks in the Great Recession, relative to the same areas before the shock and other areas that experienced smaller shocks. The upskilling of these occupations make them more palatable to higher-skilled workers. They argue that their results clarify the results of Beaudry et al. (2016) and indicate that "cognitive workers" are being drawn into (formerly) routine-task occupations as the skill content of occupations evolve.

4 Data

To study changes in local labor market inequality, we use data from the decennial U.S. Census for the years 1980, 1990, and 2000 drawn from the 5 Percent samples; and for 2005 to 2019, we make use of data from the American Community Survey (ACS). These data are downloaded from the Integrated Public Use Microdata Series (IPUMS) website directed by the University of Minnesota (Ruggles et al. 2021). The spatial unit of observation is standard metropolitan statistical areas (MSAs), which are regions consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core.¹⁶

For all of our samples, we consider only the non-farm, private sector. We draw a sample of full-time, full-year (FTFY) workers, here defined, in common with Autor et al. (2008), as those who worked 35 h or more in a week, and worked for at least 40 weeks, and were between the age of 25 and 50 years old. We draw samples for both men and women separately as well as a pooled sample,

aggregating the samples of men and women together.¹⁷ These data are then sorted into sex-education-experience groups of two sexes, five education categories (high school dropout, high school graduates, some college, college graduates, and advanced degree), and eight potential experience categories (0–5, 5–10, 10–15, 15–20, 20–25, 25–30, 30–35, and 35–40 years). Log hourly wages of full-time, full-year workers are regressed in each year separately by sex on dummy variables for five education categories, a quartic in experience, three region dummies, black and other race dummies, and interactions of the experience quartic with three broad education categories (high school graduates, some college, and college plus). The (composition-adjusted) mean log wage for each of the forty groups in a given year is the predicted log wage from these regressions. Mean log wages in each year represent weighted averages of the relevant (composition-adjusted) cell means using a fixed set of weights, equal to the mean share of total hours worked by each group over the period of 1980–2019.

We use a standard measure of college/non-college relative supply calculated in "efficiency units" to adjust for changes in labor force composition. In common with most approaches on the subject, we broaden the college category to include college graduates and those with advanced degrees. Specifically, the labor supply for college/high school groups by experience level is calculated using efficiency units, equal to mean labor supply for broad college (including college graduates and greater than college) and high school (including high school dropouts and high school graduates) categories, weighted by fixed relative average wage weights for each cell. The labor supply of the "some college" category is allocated equally between the broad college and high school categories. The fixed set of wage weights for 1980–2019 are constructed using the average wage in each of the groups (six overall samples, four education groups, and eight experience groups) over this period.

We instrument relative supply with the log ratio of supplements to wages and salaries (benefits) and the Freddie Mac House Price Index (FMHPI). Data for benefits come from the BEA regional accounts (Table CAINC30), which includes actual employer contributions and actuarially imputed employer contributions to reflect benefits accrued by defined benefit pension plan participants through service to employers in the current period and employer contributions to government social insurance. The FMHPI provides a measure of typical price inflation

¹⁶ Since 1950, the Bureau of the Budget (later renamed the Office of Management and Budget, or OMB), has produced and continually updated standard delineations of metropolitan areas for the U.S., defining each area as a county or a set of contiguous counties, or, for New England prior to 2003, as a set of cities or towns. These delineations were consistent for most of the following census years until the significant revision of metropolitan delineations in 2013 by the OMB.

¹⁷ This provides us with six total samples: an aggregated broad sample, a broad sample of men and women and similarly for FTFY workers.

for houses within the U.S. from the national level to state and metropolitan level.¹⁸

We focus on four inequality concepts: changes in overall wage inequality, summarized by the $\log p(95)-p(10)$ wage differential and the log variance of composition-adjusted wages; changes in inequality in the upper and lower halves of the wage distribution, summarized by the $\log p(95)-p(50)$ and $\log p(50)-p(10)$ wage gaps (“upper” and “lower” tail inequality), and between-group wage differentials, illustrated using the college/high school wage premium. We gather data from the Bureau of Economic Analysis’ (BEA) Regional Accounts tables to generate employment share by industry. Specifically, we use data from the Economic Profile, Table CAINC30 and Total Full-Time and Part-Time Employment by Industry, Table CAEMP25. These two tables provide us with data on the employment level of an MSA, its income, its population, among other relevant information.

We use the May data from the Bureau of Labor Statistics (BLS) *Occupational and Employment Statistics* (OES) or *Occupational Employment and Wage Statistics* (OEWS) program, which is a semiannual survey designed to produce estimates of employment and wages for specific occupations, for the years 2000 and 2005 to 2019.¹⁹ When these data are not available, we turn to our Census sample and use the occupational codes provided by IPUMS to produce estimates for occupations.²⁰ Combining the two sources, we obtain estimates for employment in finance and technology (“computer and

mathematical”) occupations.²¹ We focus on these two occupations, in particular, to complement our estimates for the demand of skilled labor (college graduates). For institutional data, we use data from Hirsch and Macpherson (2003), which provides time-consistent national and state-level estimates of union density for the years 1964 through 2018.²² We combine these with state minimum wage laws to build a data set with relevant institutional factors taken into consideration.

5 Skilled labor demand estimates

In this section, we draw upon the canonical Katz and Murphy model (Katz and Murphy 1992) supply and demand to see if there are differential relative demand shifts by MSA.²³ The canonical model posits two skill groups high and low. It draws no distinction between skills and occupations (tasks), so that high-skill workers effectively work in separate occupations (perform different tasks) from low-skill workers. In most empirical applications of the canonical model, it is convenient to identify high-skill workers with college graduates H and low-skill workers with high school graduates L . A crucial element to the two-factor model is that high and low-skill workers are imperfect substitutes in production. The total supplies of aggregate low and high-skill inputs to production are, for each MSA i in time t , respectively:

$$L_{it} = \int_{j \in \varphi} l_j n_j d_j \quad (5)$$

and

$$H_{it} = \int_{j \in \zeta} h_j n_j d_j, \quad (6)$$

where l_j or h_j reflect the efficiency units (or human capital) supplied each hour by low and high-skill labor. Specifically, each low-skill worker $j \in \varphi$ has l_j efficiency units of low-skill labor and each high-skill worker $j \in \zeta$ has h_j units of high-skill labor.

¹⁸ Freddie Mac publishes the monthly index values of the Freddie Mac House Price Index (FMHPI) each quarter. Index values are available for the nation, the 50 states, the District of Columbia, and the more than 380 metropolitan statistical areas (MSAs) in the United States. The primary differences between the FMHPI and other indices are the inclusion of some appraisal values used for refinance transactions, the choice of geographic weights, the method for identifying outliers, and the use of statistical smoothing to estimate indices more efficiently at finer geographic levels.

¹⁹ The OEWS program collects data on wage and salary workers in non-farm establishments to produce employment and wage estimates for about 800 occupations. Data from self-employed persons are not collected and are not included in the estimates. The OES program surveys approximately 180,000 to 200,000 establishments per panel (every 6 months), taking 3 years to fully collect the sample of 1.1 million establishments.

²⁰ These data are not available at the MSA level prior to 1997. Prior to that year, the OEWS program collected only occupational employment data for selected industries in each year of its three-year survey cycle, and produced only industry-specific estimates of occupational employment. The 1996 survey round was the first year that the OEWS program began collecting occupational employment and wage data in every state. In addition, the program’s three-year survey cycle was modified to collect data from all covered industries each year. 1997 is the earliest year available for which the OEWS program produced estimates of cross-industry as well as industry-specific occupational employment and wages. Hence, for the 1990 and 1980 Census, we use the IPUMS occupation codes OCC2010.

²¹ The IPUMS occupation code (OCC2010) is a harmonized occupation coding scheme based on the Census Bureau’s 2010 ACS occupation classification scheme. The 2010 occupation coding scheme for OCC has 493 categories. In the interest of harmonization, however, the scheme has been modified to achieve the most consistent categories across time. We match these categories to the 480 occupational categories in the OEWS data.

²² Two sources of data are combined to produce these estimates, the Current Population Survey (CPS) and the discontinued Bureau of Labor Statistics publication, the Directory of National Unions and Employee Associations, which is drawn on data reported by labor unions to the government.

²³ As the Katz-Murphy model is a fairly well known model, we derive only the essential formulations of the model, conforming to the metropolitan level.

The starting point is a CES production function, where output Y is produced by the two skill groups

$$Y_{it} = \left[\phi L_{it}^{\frac{\sigma-1}{\sigma}} + \psi H_{it}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad (7)$$

with parameters ϕ and ψ reflecting technology constants that determine the productivity of low and high-skill labor inputs. $\sigma \in [0, \infty]$ is the elasticity of substitution between the two education groups.

Factor-augmenting technical change is captured by changes over time in ϕ and ψ . Assuming that each MSA has a perfectly competitive labor market, equation (7) can be solved for the ratio of the marginal of the two kinds of labor, yielding the relationship between relative wages in year t . Ignoring subscripts i and t , combining the derivatives, and taking the natural log yields

$$\ln \omega = \frac{\sigma-1}{\sigma} \ln \left(\frac{\psi}{\phi} \right) - \frac{1}{\sigma} \ln \left(\frac{H}{L} \right) \quad (8)$$

This equation shows that there is a simple log linear relationship between the skill premium ω and the relative supply of skills as measured by $\frac{H}{L}$, specifically that,

$$\frac{\partial \ln \omega}{\partial \ln \left(\frac{H}{L} \right)} = -\frac{1}{\sigma} < 0 \quad (9)$$

An increase in the relative supply of skills reduces the skill premium with an elasticity of $\frac{1}{\sigma}$. Intuitively, when high and low-skill workers are producing the same good but performing different functions, an increase in the number of high-skill workers will necessitate a substitution of high-skill workers for the functions previously performed by low-skill workers.

Rearranging (8) allows us to obtain the relative demand function:

$$\ln \left(\frac{H}{L} \right) = (\sigma-1) \ln \left(\frac{\psi}{\phi} \right) - \sigma \ln \left(\frac{w_H}{w_L} \right) \quad (10)$$

which can be further simplified to reach,

$$\ln \left(\frac{w_H}{w_L} \right) = \frac{1}{\sigma} \left[D - \ln \left(\frac{H}{L} \right) \right], \quad (11)$$

where $D = \ln \left(\frac{\psi}{\phi} \right)$ indexes relative demand shifts favoring college educated workers, measured in log units. The impact of changes in relative skill supplies on relative wages depends inversely upon the magnitude of the elasticity of substitution between skilled and unskilled workers; the greater the value of σ , the smaller are the impacts of relative supply shifts on relative wages, and, consequently the greater must be changes in relative demand. For our purposes, we would like an estimate of σ at the

spatial level, so that we can construct a measure of implied relative demand at the spatial level. We can rearrange the previous equation and reintroduce subscripts to reach,

$$D_{it} = \ln \left(\frac{H_{it}}{L_{it}} \right) + \sigma \ln \left(\frac{w_{H_{it}}}{w_{L_{it}}} \right), \quad (12)$$

where spatial relative demand is the relative supply plus the product of the elasticity of substitution and the relative wage.

We employ a Two Stage Least Squares (2SLS) estimation approach where we instrument relative supply. Ciccone and Peri (2005) use data from Acemoglu and Angrist (2000) on school-attendance and child-labor laws to create instruments for the relative supply of educated workers. In a similar way, Lindley and Machin (2014) use state female college enrollment and state 18-year-old population size as instruments. We instrument relative supply with the log ratio of supplements to wages and salaries (benefits) and the Freddie Mac House Price Index (FMHPI). Data for benefits come from the BEA Regional Data, Economic Profile CAINC30) table, which includes actual employer contributions and actuarially imputed employer contributions to reflect benefits accrued by defined benefit pension plan participants through service to employers in the current period and employer contributions to government social insurance. The FMHPI provides a measure of typical price inflation for houses within the U.S. from the national level to state and metropolitan level.

We hypothesize that both the level of benefits and the state of the local housing market are strong motivating forces for the area that college graduates decide to reside upon graduating. To the discerning worker, the log ratio of the benefits level to housing prices (the FMHPI) signals the affordability of an area, and hence, is generally indicative of an area's standard of living. Firms, likewise, take into consideration whether to increase or scale down labor demand college graduates due to the associated costs incurred through additional wages supplements. Since supplements to wages and salaries are primarily driven by national changes in tax policies and group health insurance policies in the U.S., they should be unrelated to changes in local productivity. Workers, furthermore, are heterogeneous in how much they desire the various non-market amenities offered across metropolitan areas (Diamond 2016). These local non-market amenities may include, for example, the MSA's proximity to a coastline, climate, and so forth, which are exogenous factors that makes the metropolitan area different. These local non-market amenities can also include how generous are the social insurance programs in the metropolitan area, the quality of the MSA's public infrastructure, crime rates, pollution, and so on.

Table 3 First stage regressions, elasticity estimates, 1980–2019, pooled years Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019. Freddie Mac, Freddie Mac Housing Price Index (FMHPI). Bureau of economic analysis, regional data, economic profile (CAINC30)

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{benefits}/\text{FMHPI})$	0.173** (0.045)	0.131** (0.036)	0.247*** (0.064)	0.155*** (0.036)	0.109*** (0.028)	0.259*** (0.060)
Adjusted R^2	0.29	0.25	0.29	0.29	0.24	0.29
F -test	14.84***	13.18***	14.83***	18.26***	14.83***	18.46***
AR Wald test	15.51***	15.81***	15.02***	17.19***	19.62***	17.14***

The dependent variable of columns (1)–(6) is the relative supply of college graduates in efficiency units. All models include time and MSA fixed-effects. Clustered robust standard errors reported in parentheses. F -test denotes the Stock–Yogo F statistic. Asterisks (*), (**), and (***) denote statistical significance at the 10, 5, and 1% levels respectively. Each regression utilizes a sample size of 3060 observations across 170 MSAs in 18 time periods

To be able to estimate the second stage of equation (12), we need to specify the demand term in some way. To do this, let Y_{it} be our dependent variable (the college premium) and let A_{it} be a function of α_i , an MSA fixed-effect, a year effect λ_t , and an error term specific to each MSA v_{it} . The estimating equation then becomes:

$$Y_{it} = A_{it} + X_{it}\beta + \epsilon_{it}, \quad (13)$$

where $\epsilon_{it} = u_i + v_{it}$.

The year effects λ_t are specified in a general manner, using a set of year dummy variables, so that the estimating equation expresses the relative wage of skilled workers as a function of time, the MSA effect, and relative supply X for each MSA.

The first stage regression is then,

$$X_{it} = \alpha_i + \lambda_t + Z_{it}\gamma + u_{it} \quad (14)$$

The specification of an instrumental variables model asserts that the excluded instruments affect the dependent variable only indirectly through their correlations with the included endogenous variables. If an excluded instrument exerts both direct and indirect influences on the dependent variable, the exclusion restriction should be rejected. With one endogenous variable, the F -statistic in the first stage regression, which Staiger and Stock (1997) suggest should be greater than 10: from our first stage results, we see that they appear to muster this test. Furthermore, in an exactly identified model, as in the present case, we cannot test the hypothesis that the instrument is valid, i.e. that the exclusion restriction is a valid one.

5.1 Elasticity estimates

Estimates from 2SLS models (reported in Table 4) are weighted by the employment share of college graduates and estimated with clustered standard errors. Instrumental variables methods rely on two assumptions: the excluded instruments are distributed independently of

the error process, and they are sufficiently correlated with the included endogenous variables. Our choice of instruments appear to be strong instruments as indicated by the first stage regressions represented in Table 3.

The Staiger and Stock rule of thumb test is not robust to weak instruments. To further check against this potential dilemma, we rely on the Anderson–Rubin (AR) test robust inference for testing the significance of the endogenous regressors in the structural equation being estimated (Anderson and Rubin 1949). The null hypothesis tested is that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero, and, in addition, that the overidentifying restrictions are valid. The test is robust to the presence of weak instruments and is equivalent to estimating the reduced form of the equation (with the full set of instruments as regressors) and testing that the coefficients of the excluded instruments are jointly equal to zero. In all cases, we reject the null hypothesis and conclude the instrument is not weak.

Column 1 of Table 4 shows estimates for the pooled sample of men and women, column 2 shows those estimates for men only, and finally, column 3 display estimates for women.²⁴ The estimates indicate that the elasticity of substitution for the pooled sample (both men and women) is 2.11 $\left(\frac{1}{0.475}\right)$, 1.65 for men, and 2.87 for women. These estimates are within the range of those obtained at the aggregate national level by Autor et al. (2008). For FTFY workers, the estimate are 2.12, 1.60, and 3.26 for the pooled sample, men, and women respectively. The elasticity estimates of Lindley and Machin (2014) differ from the estimates obtained here, which may have to do with their larger sample size and selection (in terms of number of metropolitan areas per year) as well as with the composition adjustment they make to wages sampled in their study. Our estimates are closer to

²⁴ Columns in the first stage regressions map to the same.

Table 4 FE-2SLS elasticity estimates, 1980–2019, pooled years Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

	Pooled FTFY (1)	FTFY Men (2)	FTFY Women (3)	Full Pooled (4)	Full Men (5)	Full Women (6)
Relative supply	−0.471*** (0.024)	−0.626*** (0.050)	−0.307*** (0.013)	−0.475*** (0.022)	−0.605*** (0.042)	−0.349*** (0.013)
Adjusted R^2	0.76	0.60	0.74	0.78	0.64	0.74

Dependent variable is the log of the composition adjusted college–high school wage differential. The log ratio of supplements to wages and salaries and the Freddie Mac Housing Price Index (FMHPI) is used as an instrument for relative supply. All models estimated with MSA and year fixed-effects. Estimates are weighted by inverse sampling variance. Standard errors are in parentheses. Asterisks (*), (**), and (***) denote statistical significance at the 10, 5, and 1% levels respectively

those obtained by Fortin (2006), who estimated σ to range from 4.39 and 5.68 for a state level sample of workers between the ages of 26 and 35 from 1979 to 2002.²⁵ As noted by Autor et al. (2008), the Katz–Murphy model does an excellent job forecasting the growth of the college wage premium, but the continued slow growth of relative supply after 1990 leads it to slightly over-predict the growth in the college wage premium in the 2000s.

5.2 Local area labor demand

We are now able to combine the spatial changes in the college wage premium and relative supply into an implied relative demand index using the estimates of σ . Recall earlier that A_{it} was specified to be some function of α_i , an MSA fixed-effect, a year effect λ_t , and an error term specific to each MSA v_{it} .

This can be written as:

$$D_{it} = \phi + \sigma\theta$$

where ϕ is the relative supply of college educated workers to high school educated workers and θ is the relative wage (wage premium) of college educated workers. Computing this index reveals substantial differences in relative demand for college educated workers across metropolitan areas but also reveals persistence in relative demand for college educated workers in certain metropolitan areas. Table 5 compares the estimates for different values of σ from regressions on the relative demand shifts for the time periods 1980–1990, 1990–2000, 2000–2010, and 2010–2019. To further see how the relative demand for college workers changed within each decade, we may write:

$$\nabla D_{it} = \frac{1}{n} \sum_{i=1}^n (D_{it} - D_{it-1}) \quad (15)$$

∇D_{it} gives the average change in relative demand for college workers across all MSAs for the given time periods. This can be estimated with the regression equation:

$$D_{it} = a + \zeta D_{i,t-1} + \eta_{it}, \quad (16)$$

which is a general OLS equation with a as the intercept, ζ the parameter of interest, η_{it} an error term. $D_{i,t-1}$ is the lagged demand index ($t-1$) of equation (15) for MSA i . We estimate this equation for each period t following 1980; thus, we estimate for the period 1980–1990, 1990–2000, 2000–2010, and lastly for the period 2010–2019. Table 5 reports these estimates and compares the average of our estimates of σ with those obtained by Fortin (2006) and Autor et al. (2008). These estimates show that the results are comparable with varying estimates of σ . Furthermore, given that our estimates of relative demand depend on our elasticities of substitution, which in turn depend on the validity of our instruments, these comparisons check for the robustness of our results.

Compared with the 1980s the relative demand for college graduates has increased across all time periods although these changes get smaller over time. The first row in Table 5 shows these for our estimated σ values and reveals that putting together the relative supply and relative wage measures to compute this demand index in this way produces a pattern of highly persistent relative demand shifts at the spatial level. The persistence is especially strong in the 1990–2000 and 2010–2019 periods, where the estimate is greater than 1.

5.3 Shifts in demand and supply

Combining our estimates of σ with the data, we present how relative demand and supply varied by gender in the considered time period. These estimates are presented in Table 6. The tabulated statistics show that, among FTFY workers, men fared better in terms of relative wage growth during the early part of the considered period (1980 to 2000). Table 6 also shows that demand for skilled labor has cooled since the early part of the period: across all major groups, relative demand was notably smaller in magnitude

²⁵ Empirical studies adopting Katz and Murphy's model have found similar estimates of the elasticity of substitution: Ciccone and Peri (2005) 1.5 using a sample of white men between 40 and 50 years of age, Autor et al. (2008) obtain 1.57 for full-time-full-year workers, and Lindley and Machin (2014) 2.94 for MSAs.

Table 5 Spatial-temporal dependence in relative demand Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

	Estimates of ζ from $D_{it} = a + \zeta D_{i,t-1} + \eta_{it}$			
	1990–1980	2000–1990	2010–2000	2019–2010
Eisenbarth-Chen estimates, $\hat{\sigma} = 4.15$	0.843*** (0.021)	1.108*** (0.033)	0.869*** (0.027)	1.103*** (0.027)
Autor et al. (2008), $\hat{\sigma} = 2.40$	0.841*** (0.021)	1.109*** (0.033)	0.870*** (0.027)	1.102*** (0.027)
Fortin (2006), $\hat{\sigma} = 5.68$	0.842*** (0.020)	1.113*** (0.033)	0.869*** (0.027)	1.109*** (0.026)

The dependent variable is the implied relative demand shift log and the explanatory variable is the implied relative demand shift in the previous decade $t - 1$. Presented author estimates an average of estimates of the elasticity of substitution as described in text. Standard errors are reported in parentheses beneath the estimates. Asterisks (*, **, ***) denote statistical significance at the 10, 5, and 1% levels

after 2010 as compared with earlier. This may be due in part to the sluggish recovery following the Great Recession. In particular, the shift in the Beveridge curve and the shock to the hiring rate undoubtedly factors in largely. Barnichon et al. (2012) find that the Beveridge curve did shift for the United States after the Great Recession in 2009 and that the shift was caused by a decline in hires per vacancy expected at the relevant level of unemployment.²⁶

To see more clearly the differences in relative demand for college workers, we present figures to show the spatial distribution of the demand shift measure: these show that the relative demand shift has strongly favored college workers, but also, these shifts tend to favor larger MSAs (see Fig. 4). The plots display remarkable spatial persistence in relative demand for college graduates in larger metropolitan areas. In particular, MSAs that have high and persistent demand for college educated workers are MSAs such as San Jose, Boston, San Francisco, Washington D.C., and New York (see Table 1). These areas are well known for exhibiting agglomeration effects through the clustering of certain industries: software and computer technology, for example, in San Jose.

In contrast, MSAs that experienced lower shifts in demand for skilled labor tended to have higher manufacturing employment in 1980 (the start of our sample). Elkhart-Goshen, Indiana; Mansfield, Ohio; Hickory, North Carolina; and Lancaster, Reading, and York-Hanover of Pennsylvania are MSAs that were heavily concentrated in manufacturing and tended to experience lower

²⁶ Davis et al. (2012) also find fewer hires than expected in the period since recovery from the Great Recession officially began. They also find evidence of considerable variation across employers in their ability, or inclination rather, to fill vacancies. These results suggest that something about the manner in which firms are recruiting and selecting candidates may explain why vacancies last longer. This is related to the findings of Molloy et al. (2016) who suggest that the U.S. has experienced a decline in labor market “fluidity”—an index they compile from transitions into and out of employment and job-to-job transitions, job creation and job destruction rates, and interstate migration—which has decreased by 10% to 15%, by their estimates, since the 1980s.

Table 6 Changes in relative demand, supply, and earnings Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

	1980–1990	1990–2000	2000–2010	2010–2019
<i>Pooled</i>				
Demand	8.5	8.4	13.5	−0.1
Relative wage	17.9	8.2	10.7	0.8
Supply	2.7	5.7	10.0	−0.4
<i>Men</i>				
Demand	8.1	9.8	12.6	−0.4
Relative wage	18.9	10.2	7.9	5.0
Supply	0.2	5.5	9.3	−2.5
<i>Women</i>				
Demand	5.6	5.2	11.3	0.5
Relative wage	16.5	5.5	14.4	−4.4
Supply	1.9	4.0	8.1	1.5

Tabulated numbers are changes in the (composition-adjusted) mean log wage for each group, using data on full-time, full-year workers ages 18 to 18 covering 1980 to 2019. These data are sorted into sex-education-experience groups of two sexes, four education categories (high school dropout, high school graduate, some college, college graduate, and post-college), and eight potential experience year groups (0–5, 5–10, 10–15, 15–20, 20–25, 25–30, 30–35, and 35–40 all measured in potential years of experience). Log hourly wages of full-time, full-year workers are regressed in each year separately by sex on dummy variables for four education categories, a quadratic in experience, three region dummies, black and other race dummies, and interactions of the experience quadratic with three broad education categories (high school graduate, some college, and college plus)

demand shifts for college graduates. These areas are notably in the Rust Belt region of the U.S., the plight of which following de-industrialization has been widely documented, both in academic literature and popular media.²⁷ Other areas such as Brownsville-Harlingen, Texas, Visalia-Porterville, California, and Yakima, Washington also experienced lower demand shifts.

²⁷ Since the term “Rust Belt” is used to refer to a set of economic and social conditions rather than to an overall geographical region of the United States, the Rust Belt has no precise boundaries.

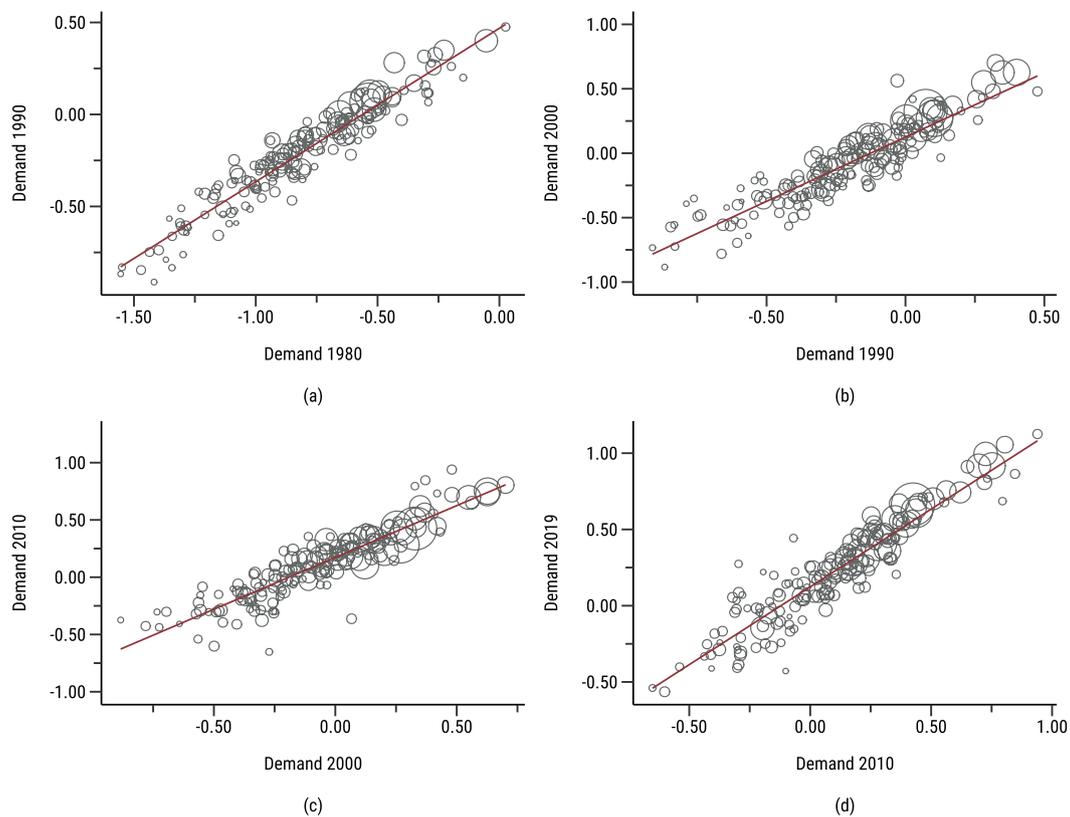


Fig. 4 Implied demand shifts, 1980, 1990, 2000, 2010, 2019. Bubble size reflects population size in 1980. Fitted regression lines are fit by ordinary least squares Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

5.4 Skilled labor demand correlates

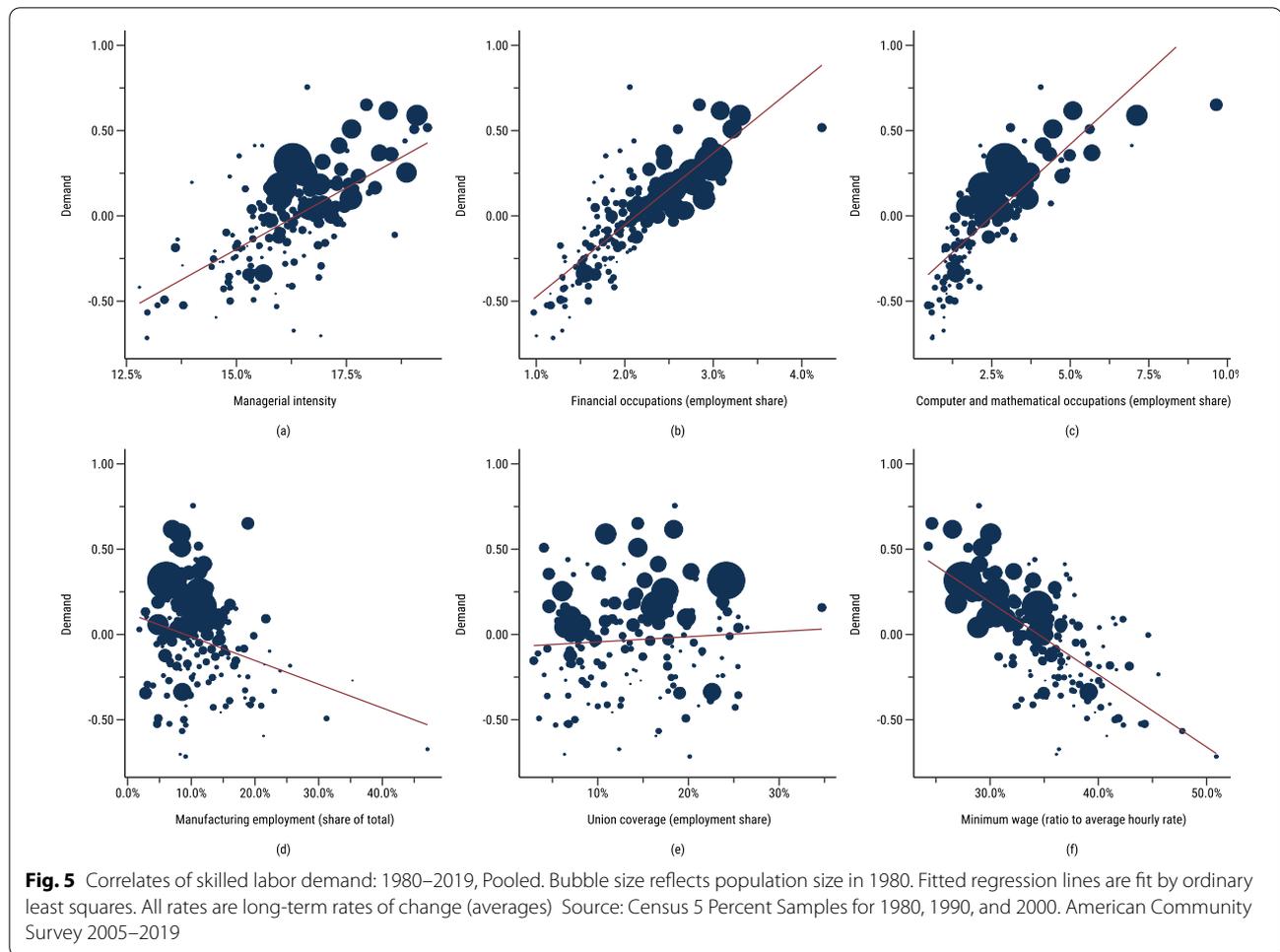
We can further relate our estimates of implied demand to variables that may influence the demand of college graduates, these include the proportion of workers covered by collective bargaining agreements (union density), the minimum wage, manufacturing employment, and managerial intensity or the proportion of the workforce employed in managerial and supervisory positions. We also check the relationship between implied demand and employment in finance and technical occupations.²⁸ From the standpoint of the simple Katz-Murphy model, skilled labor demand should be highly correlated with increases in these two occupational categories. We plot these relationships (Fig. 5a–f) allowing us to visually inspect how institutional and labor market forces are related to changes in relative demand for college graduates. Implied demand estimates are strongly associated with managerial intensity, technology, and financial occupation

²⁸ We obtain estimates for these occupations using a combination of the IPUMS OCC2010 occupation code and the OEWS occupation codes. The OEWS codes are adopted from the Standard Occupational Classification (SOC) system. Technical occupations are defined by the detailed OEWS codes in the range of 15–1000 to 15–2098. We similarly defined finance occupations as being in the range of 13–2000 to 13–2098 for “Financial Specialists.”

specialization. With respect to manufacturing employment, labor demand for college graduates appears to have a markedly negative linear relationship as seen in Fig. 5d.

In the approximate forty-year period we study, increases in relative demand were faster in MSAs with higher degrees of managerial intensity and where employment in technical occupations is more intensive. At the same time, MSAs where manufacturing has fallen by more have also seen slower demand shifts in favor of more educated workers. Such patterns appear to be akin to the predictions of the model presented by Autor and Dorn (2013).²⁹ Union density and the minimum wage appear to have little effect on the demand of skilled workers: the smoothed line is nearly horizontal when considering union coverage and only has a slight upward bent when considering the minimum wage. These

²⁹ Their model predicts that labor markets historically specialized in routine task-intensive industries should: (1) differentially adopt computer technology and displace workers from routine task-intensive occupations; (2) undergo employment polarization as low-skill labor is reallocated to low-task-intensive in-person services; (3) exhibit larger wage growth at both ends of the occupational skill distribution (wage polarization); and (4) experience larger net inflows of workers with both high and low educational levels driven by rising demand for both.



patterns appear to suggest that institutional factors have little influence on the demand for skilled workers.

6 Local area wage inequality

Using the IPUMS data, we calculate measures of wage inequality and various measures of labor force composition for each of the local areas that are included in our sample for the 1980–2019 period. In particular, we are interested in the effect of managerial intensity M on wage inequality. Our causal assumption regarding managerial intensity is related fundamentally to the efficiency wage model discussed earlier. More specifically, our causal assumptions align more with the Bowles–Gintis version of the efficiency wage model (see for example, Rebitzer 1987; Green and Weisskopf 1990) rather than the Shapiro–Stiglitz interpretation. In which case, an increase in managerial intensity should lead to an increase in wage dispersion.

To address this question, let Y_{it} be the observed value for wage inequality for MSA i in time t . Suppose that the effects of managerial intensity are additive and constant

and let A_{it} be a measure of unobserved components, we have a standard fixed-effects model,

$$Y_{it} = D_i + \gamma_t + \zeta M_{it} + X'_{it}\beta + u_{it}, \tag{17}$$

where u_{it} is assumed to be iid over i and t , and ζ is the effect of interest.³⁰

The parameter D_i captures unobserved heterogeneity among the metropolitan areas and γ_t a vector of time dummies; the unobserved individual effects are coefficients on dummies for each individual MSA while the year effects are coefficients on time dummies. Through this treatment, we can estimate the causal effect of managerial intensity on residual wage inequality.

The model assumes that Y_{it} is a function of exogenous factors, X_{it} , while the conventional analysis of variance (ANOVA) model stipulates that the expected value of Y_{it}

³⁰ It is perhaps more appropriate to call models of this sort an Unobserved Effects Model (UEM) in line with Wooldridge (2002) since the treatment of whether the effects are “fixed” or “random” lies more in how the researcher views how the unobserved components affect Y_{it} (Angrist and Pischke 2009).

depends only on the MSA (or “group”), i , to which the observation considered belongs and that the value of the measured quantity, Y_{it} , assumes the relation that $Y_{it} = \alpha_i + \epsilon_{it}$, where the effects of all other characteristics, ϵ_{it} , are random and are in no way dependent on the individual-specific effects, α_i . But if Y_{it} is also affected by other variables that we are not able to control and standardize within-groups, the within-group sum of squares will be an overestimate of the stochastic component in Y_{it} . Consequently, the differences between-group means will reflect not only any group effect but also the effects of any differences in the values assumed by the uncontrolled variables in different groups (Hsiao 2014).

We fit specifications to this general form using the log residual variance of composition-adjusted hourly wages as the dependent variable Y_{it} . Our baseline model is a pooled OLS model, where we regress wage inequality against union density, manufacturing employment, managerial intensity, and estimated labor demand for college graduates. Additionally, we include dummy variables for regional specialization in finance and technology occupations, and a dummy variable for any MSA where the immigrant labor share is equal or greater than 20%. To account for heterogeneity, we estimate models using clustered robust standard errors. Failure to control for within-cluster error correlation can lead to misleadingly small standard errors, and consequently misleading confidence intervals, large t -statistics and low p -values.

To account for agglomeration effects through regional clustering of the finance and technology industries, we estimate the location quotient (LQ) for our sample of MSAs for these occupations.³¹ We limit our estimation of location LQs for regional specialization to technology and finance. We construct dummy variables based upon the LQ coefficient's value where the dummy is equal to 1 if the LQ coefficient is greater than 1 and 0 otherwise; this provides a categorical variable where “1” indicates regional specialization.

We include the share of total employment in durable goods manufacturing and in non-durable goods manufacturing, expecting to find that larger shares of both types of manufacturing are associated with lower inequality. Managerial intensity is the ratio of managerial and supervisory employees to non-supervisory employees for the private, non-farm sector for each MSA. The delineation of managerial and supervisory employees were established through Census occupation codes in the line of Gordon (1994). We expect to find a positive relationship between managerial intensity and inequality. We include the union coverage rate at first at the MSA level and the state level where this data is not available at the

MSA level from the Hirsch and Machperson database.³² From our demand index construction, we include the estimated demand shifts for each MSA. And lastly, we use publicly available state minimum wage laws to construct a variable (the ratio of the state minimum wage to the estimated average hourly wage at the MSA level) to capture the effect of the minimum wage.

6.1 Results

Our estimates are reported in Table 7. Column 1 reports the baseline OLS estimates, Columns 2 and 3 reports fixed-effects estimates. Our preferred estimates are the fixed-effects estimates in the third column. We reduce the model by culling independent variables that are not statistically significant within acceptable confidence intervals; this provides a reduced model of 5 independent variables.

The effect of the main variable of interest, managerial intensity, is both positive and statistically significant at the 5% level in all model specifications. Similarly, the estimates for technology occupations (computer and mathematical), are positive and statistically significant in all specifications. Along these estimates, it is interesting to note the statistically insignificant effect of the skilled labor demand index and the specialization of finance occupations. On the whole, this seems to support the predictions of Gordon's extension of the Bowles–Gintis model.

The effect of manufacturing employment is estimated to be negative and statistically significant, suggesting that wage inequality tends to be lower in areas with denser manufacturing intensity. The estimate for the immigrant share is positive and statistically significant. A plausible reason for the positive coefficient for the immigrant share of employment is that immigrants to the U.S. typically possess much lower educational attainment levels than native-born citizens. And furthermore, they are more likely to work in low-wage, low-skill occupations than native-born citizens. Although the presence of immigrants may put downward pressure on low-skilled citizens wages, we caution against this interpretation given that the effects of immigration are mixed (see for instance, LaLonde and Topel 1991; Ottaviano and Peri 2012).

We can calculate how much a one standard deviation increase in our independent variables of the reduced model can account for using clustered robust standard errors. The equation used for this is $\frac{\hat{\beta}_i \sigma(X_i)}{\sigma(Y)}$, where x is understood to be the independent variable i , and $\hat{\beta}_i$ the estimated coefficient, and Y the residual wage dispersion measured by the log variance of the composition adjusted wages. The ranges of magnitudes within a 95% confidence interval that emerge from the reduced model are: managerial intensity, 0.35% to 10.5%;

³¹ The location quotient is $\frac{e_{ij}}{e_j} \setminus \frac{E_j}{E}$ where e_{ij} is total employment in industry or occupation j in region i , e_j total employment in region i , and E_j and E , their equivalents at the national level.

³² The Hirsch–Machperson estimates are not available at the metropolitan level before 1986. Furthermore, estimates are not consistently available for all metropolitan areas. Further details are available at the [Union Membership and Coverage Database \(Unionstats.com\)](http://www.unionstats.com).

Table 7 Determinants of wage dispersion, pooled years Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019. Union Membership and Coverage Database, State and Metropolitan Estimates 1980–2019. Occupational Employment and Wage Statistics 2000–2019. U.S. Department of Labor, State Minimum Wage Laws, Historical Tables. Bureau of Economic Analysis, Regional Data, Total Full-Time and Part-Time Employment by Industry (CAEMP25), Economic Profile (CAINC30)

	Pooled OLS	Fixed-effects	Fixed effects (reduced model)
	(1)	(2)	(3)
Manufacturing	−0.071*** (0.042)	−0.082*** (0.028)	−0.089*** (0.027)
Managerial intensity	0.212*** (0.110)	0.099** (0.030)	0.102*** (0.030)
Finance	0.002 (0.545)	−0.036 (0.134)	
Immigrant share	0.226*** (0.031)	0.155*** (0.019)	0.150*** (0.027)
Technology	0.334*** (0.086)	0.195** (0.102)	0.222*** (0.097)
Union coverage	−0.050*** (0.027)	0.018 (0.014)	
Minimum wage	−0.175*** (0.030)	−0.016* (0.010)	−0.131** (0.010)
Demand	0.071*** (0.008)	0.010 (0.006)	
Constant	0.292*** (0.029)		
Adjusted R^2	0.59	0.61	0.60
F-Statistic	108.09	16.49	21.82

A total of $n = 170$ metropolitan statistical areas over $t = 18$ time periods. Samples include persons between the ages of 18 and 65 years old, currently employed and worked in the prior year. Wage inequality is measured as the log residual variance of real weekly earnings of all non-self-employed workers. Clustered robust standard errors are reported beneath in parentheses. Critical F values depend on $df(9; 170)$, $df(8; 169)$, and $df(8; 169)$ respectively. Asterisks (*, **, ***) denote statistical significance at the 10, 5, and 1% levels

manufacturing employment, −24.85% to −6.13%; technology occupations, 1.55% to 20.65%; immigrant workforce share 24% to 51%; and the minimum wage ratio −6.15% to 0.01%.³³

Figure 6 shows the spatial aspects of these empirical connections between the MSA level wage inequality measure and the variables we consider, by plotting long-run 1980–2019 spatial wage inequality against

³³ The effect of the magnitudes are derived from the 95% confidence interval of the estimated slope coefficient for the variable of interest, constructed by using the clustered robust standard errors. The interval estimation for the estimated slope is then $\hat{\beta}_i \pm t(\hat{\beta}_i) \cdot s(\hat{\beta}_i)$, where $s(\hat{\beta}_i)$ is the clustered robust standard error of the estimated coefficient, and $t(\hat{\beta}_i)$ the critical t -statistic.

six potential factors connected to inequality. Presenting the empirical associations in this form enables us to see which MSAs are the most and least correlated with these factors. Of the metropolitan areas we consider, the Bridgeport-Stamford-Norwalk metropolitan area has the largest long-run increase in residual wage inequality, followed closely by New-York-Newark-Jersey City, Santa-Cruz-Watsonville, San-Jose-Sunnyvale, and San-Francisco-Oakland. Conversely, Sheboygan, Wausau, and Eau-Claire (all of Wisconsin), Mansfield, Ohio and Johnstown, Pennsylvania had the lowest long-run increase in wage inequality.

The areas which saw the largest increases in wage inequality tend to have: (1) deeper managerial intensity ratios (Fig. 6c); (2) a higher long-run shift in demand for college graduates (the proxy for skilled-labor) as shown in Fig. 6f; (3) a larger long-run increase in technical occupations (Fig. 6e); and (4), tended to have lower levels of manufacturing employment (Fig. 6a). The long-run decline in union coverage appears to have little relationship with wage inequality; the fitted line in Fig. 6b is approximately horizontal and this is confirmed by our estimates in Table 7. This pattern is difficult to interpret but may be motivated by profound recent changes in the composition of the unionized workforce as reported by Card et al. (2018), who find that the impact of unions on wage inequality has declined due to the shifting composition of union jobs toward the public sector. Historically, union jobs were concentrated among low-skilled men in private sector industries, half of unionized workers are now in the public sector, the majority of which are women.³⁴ Since our sample only considers the private sector, the profound changes in the composition of union jobs is perhaps the best explanation. And lastly, the minimum wage (Fig. 6d) appears to possess the expected negative relationship with wage inequality as documented by Lee (1999) and Autor et al. (2016), although this is not borne out by the results in Table 7.

6.2 Alternative measures

We extend these specifications (Table 8) to study the impact of these factors on “lower” tail inequality measured by the $\log p(50)-p(10)$ ratio, upper tail inequality measured by the $\log p(95)-p(50)$ ratio, and overall inequality measured by the $\log p(95)-p(10)$ ratio. Additionally, we also consider the impact on between log

³⁴ Card et al. (2018) find striking differences between the private and public sectors in the effects of unionization on male and female wage inequality. These differences have become more pronounced over time as private and public sector unionization have diverged. They estimate that the overall effects of unions on the economy-wide wage structure are modest in size—reductions in male wage inequality of 3.5% in the U.S. and female inequality of 3.4%. Furthermore, disaggregating by sector of employment yields striking differences: reductions in male wage inequality in the private sector of 1.7% in the U.S. and female wage inequality by 0.6%.

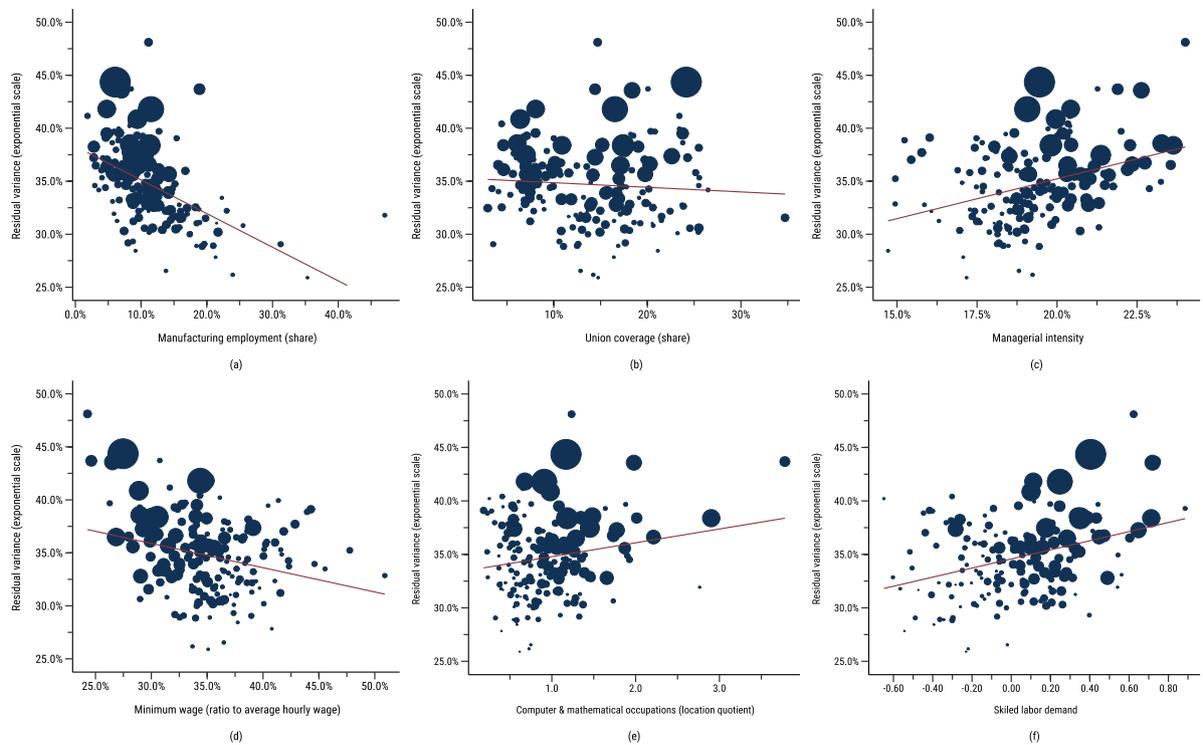


Fig. 6 Residual wage dispersion, key factors: 1980–2019, pooled. Bubble size reflects population size in 1980. Fitted regression lines are fit by ordinary least squares. All rates are long-term rates of change (averages) Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019

ratio of the 95th and 90th percentile $\log p(95) - p(90)$. We constrain our model specifications to “two-way” fixed-effects, with dummy variables for time and metropolitan area. The slope estimates are broadly consistent with those in the residual variance specifications. Labor demand for college graduates is found to be statistically significant in all specifications at standard levels of confidence, except for the upper end (between the 95 and 90th percentiles).

Based on these estimates and the actual changes in managerial employment over the period 1980–2019, on average, changes in managerial intensity account for 5% and 9% of the changes in upper tail inequality (measured by the $\log p(95) - p(50)$ and $\log p(95) - p(95)$), 5.7% for the lower tail, and 5.1% for the overall measure in local areas over this period. Comparing the results across the wage distributions, we see that the effect of managerial intensity is more pronounced at the upper end of the distribution. More importantly, the estimated coefficient for the demand for skills is not statistically significant for the gap between the $\log p(95) - p(90)$ ratios. It is interesting to note that union coverage is not statistically significant in these specifications. The effect of the minimum

wage, similarly, is found to be statistically significant for only the lower tail of the wage distribution and overall distribution. Intuitively, this result is sensible due to the fact that those at the upper percentiles are unlikely to be adversely affected by the changes in the minimum wage.

6.3 Limitations

The aim of fixed-effects is to mitigate the effects of unobservable attributes, particularly endogeneity caused by time. However, omitted variables such as the macroeconomic conditions of the region could still potentially inflict omitted variable bias on our models. Additional sources of confounding factors could stem from public policy constraints prohibiting the building up of infrastructure or cultural and social practices specific to the local labor market. For example, the Ivy League universities of the Northeast and the social networks associated with these elite institutions could influence hiring practices through network effects (Zimmerman 2019).

Although they control for a certain type of omitted variable, fixed-effects estimates are notoriously susceptible to attenuation bias from measurement error. On one hand, variables like managerial status tend to be persistent (a worker who is a manager this year is most likely

Table 8 Determinants of wage dispersion (percentiles), pooled years Source: Census 5 Percent Samples for 1980, 1990, and 2000. American Community Survey 2005–2019. Union Membership and Coverage Database, State and Metropolitan Estimates 1980–2019. Occupational Employment and Wage Statistics 2000–2019. U.S. Department of Labor, State Minimum Wage Laws, Historical Tables. Bureau of Economic Analysis, Regional Data, Total Full-Time and Part-Time Employment by Industry (CAEMP25), Economic Profile (CAINC30)

	ln 50–10 (1)	ln 95–50 (2)	ln 95–10 (3)	ln 95–90 (4)
Manufacturing	0.014 (0.023)	−0.212*** (0.047)	−0.175*** (0.061)	−0.051*** (0.022)
Managerial intensity	0.112* (0.083)	0.201** (0.100)	0.336** (0.100)	0.194** (0.070)
Immigrant share	0.029*** (0.003)	0.035*** (0.004)	0.081*** (0.020)	−0.002 (0.002)
Finance	−0.028** (0.006)	0.006** (0.002)	0.001 (0.003)	0.002 (0.001)
Technology	0.001 (0.003)	−0.010*** (0.003)	−0.008** (0.004)	0.003 (0.002)
Union coverage	0.013 (0.027)	−0.013 (0.032)	−0.000 (0.040)	−0.018 (0.019)
Minimum wage	−0.429*** (0.040)	0.040 (0.020)	−0.511*** (0.060)	−0.055 (0.025)
Demand	0.048*** (0.011)	0.028** (0.011)	0.045* (0.014)	0.011 (0.007)
Adjusted R^2	0.43	0.79	0.87	0.43
F Statistic (8; 170)	8.97***	2.77***	7.05***	3.13***

A total of $n = 170$ metropolitan statistical areas over $t = 18$ time periods. Samples include persons between the ages of 18 and 65 years old, currently employed and worked in the prior year. Clustered robust standard errors are reported beneath in parentheses. Asterisks (*, **, ***) denote statistical significance at the 10, 5, and 1% levels

a manager next year). On the other hand, measurement error often changes from year-to-year (managerial status may be misreported or miscoded this year but not next year). Therefore, while managerial and supervisory status may be misreported or miscoded for only a few workers in any single year, the observed year-to-year changes may be mostly noise.

A further element to consider is the potential endogeneity of our factor of interest. Managerial intensity might very well be increasing due to the increased integration of the workforce in terms of gender and race. Indeed, differential access to managerial jobs is one of inequality's linchpins, as these positions secure higher average wages and other rewards for their incumbents than do other jobs. Besides spawning expansive literature, the question of access to managerial jobs for protected groups has also been the focus of countless gender and race

discrimination lawsuits, formed the basis of numerous government reports, and made the term “glass ceiling” a popular term. But this has limitations, as most managers tend to be non-Hispanic white males, a historical pattern that strongly persists and which may, in fact, stem from the longstanding, biased hiring decisions of firms within the United States (see Stainback and Tomaskovic-Devey 2009; Giuliano et al. 2009). Managerial employment, moreover, could potentially stem from an additional non-random process, as managers and supervisors are selected non-randomly from the population of workers. Individual choices made by workers, such as choice of collegiate degree, can also affect the future employment prospects and access to supervisory roles.

Lastly, we are unable to interpret our estimates as strictly causal estimates of treatment effects. The aim of standard statistical analysis, typified by regression, estimation, and hypothesis testing techniques, is to assess parameters of a distribution from samples drawn of that distribution. With the help of such parameters, one can infer associations among variables, estimate beliefs or probabilities of past and future events, as well as update those probabilities considering new evidence or new measurements. These tasks are managed well by standard statistical analysis so long as experimental conditions remain the same.³⁵

7 Conclusion

Wage inequality has risen considerably since the 1980s, but there are also significant disparities with which it has grown between local areas. Using data from the U.S. Census and America Community Survey, we study several factors surrounding local labor market inequality in 170 Metropolitan Statistical Areas (MSAs) between 1980 and 2019. One contribution has been to provide estimates of the elasticity of substitution between skilled and unskilled workers at the metropolitan level. Our instrumental variables analysis finds that the substitution of elasticity between college graduates and high school workers ranges from 2.11 for a pooled sample (both men and women), 1.65 for men, and 2.87 for women. These estimates are comparable to those obtained at the aggregate national level by Autor et al. (2008). For full-time, full-year (FTFY) workers, the estimates are 2.12, 1.60, and 3.26 for a pooled sample, men, and women respectively.

Using fixed-effects models, we confirm David Gordon's thesis regarding wage inequality and managerial employment. On average, changes in managerial intensity

³⁵ A distribution function cannot tell us how that distribution would differ if external conditions were to change because the laws of probability theory do not dictate how one property of a distribution ought to change when another property is modified. This information must be provided by causal assumptions which identify relationships that remain invariant when external conditions change: behind every causal conclusion there must lie some causal assumption that is not testable in observational studies.

between 1980 and 2019 account for 6.9% of the change in wage inequality as measured by the residual variance; this effect is robust to alternative measures of wage inequality. Furthermore, managerial intensity is strongly correlated with implied demand shifts suggesting a phenomenon of “reskilling” among managerial and supervisory employees with managerial employees earning college degrees.

We offer an interpretation of our results that combines the empirical findings of the labor market polarization literature with the theoretical conceptions of labor process theory and Gordon’s labor control thesis. Starting out with the premise that technological innovation is simultaneously skill enhancing and replacing, the empirical findings of simultaneous growth in “low skill” routine labor and high-skill employment and wage growth suggest that the deskilling/reskilling hypothesis is a cogent explanation for such trends. But it alone does not account for the growth in managerial and supervisory employment and compensation.

Acknowledgements

We thank the University of Utah and the University of Missouri-Kansas City for funding travel to the 45th Annual Conference of the Eastern Economic Association as well as the generous feedback of participants. The authors would also like to thank the anonymous referees and the Editor for their constructive comments that improved the quality of this paper.

Authors’ contributions

AE and ZFC conceived the study. ZFC investigated the relationship between the labor force composition and managerial versus non-managerial employment at the metropolitan level. AE wrote the programs and analyzed the data. Both authors determined the steps of the empirical analysis and wrote the manuscript. Both authors read and approved the final manuscript.

Funding

The authors acknowledge financial support from the University of Utah and the University of Missouri–Kansas City.

Data availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interests

The authors declare that they have no competing interests.

Author details

¹Department of Economics, University of Utah, 260 South Central Campus Drive, Gardner Commons Suite 4100, Salt Lake City, UT 84102, USA. ²Department of Economics, University of Missouri–Kansas City, 5120 Rockhill Road, 211 Haag Hall, Kansas City, MO 64110, USA.

Received: 19 April 2020 Accepted: 25 February 2022

Published online: 30 March 2022

References

- Acemoglu, D.: Directed technical change. *Rev. Econ. Stud.* **69**(4), 781–809 (2002)
- Acemoglu, D.: Technical change, inequality, and the labor market. *J. Econ. Lit.* **40**(1), 7–72 (2002)
- Acemoglu, D., Angrist, J.: How large are human-capital externalities? Evidence from compulsory schooling laws. *NBER Macroecon. Annu.* **15**, 9–59 (2000)
- Acemoglu, D., Autor, D.: Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D. (eds.) *Handbook of Labor Economics*, pp. 1043–1171. Elsevier, Amsterdam (2011)
- Akerlof, G., Yellen, J. (eds.): *Efficiency Wage Models of the Labor Market*. Cambridge University Press, Cambridge (1987)
- Anderson, T.W., Rubin, H.: Estimators of the parameters of a single equation in a complete set of stochastic equations. *Annu. Math. Stat.* **1**(21), 570–582 (1949)
- Angrist, J., Pischke, J.-S.: *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton University Press, Trenton (2009)
- Autor, D.: The “task approach” to labor markets: an overview. *J. Labour Mark. Res.* **1**(46), 185–199 (2013)
- Autor, D., Dorn, D.: The growth of low skill service jobs and the polarization of the us labor market. *Am Econ. Rev.* **103**(6), 2121–2168 (2013)
- Autor, D., Katz, L.: Changes in the wage structure and earnings inequality. In: Ashenfelter, O., Card, D. (eds.) *Handbook of Labor Economics*, pp. 1463–1555. Elsevier, Amsterdam (1999)
- Autor, D., Katz, L., Kearney, M.: Trends in us wage inequality: revising the revisionists. *Rev. Econ. Stat.* **90**(2), 300–323 (2008)
- Autor, D., Katz, L., Krueger, A.: Computing inequality: have computers change the labor market? *Q. J. Econ.* **113**(4), 1169–1213 (1998)
- Autor, D., Levy, F., Murnane, R.: The skill content of recent technological change: an empirical exploration. *Q. J. Econ.* **118**(4), 1279–1333 (2003)
- Autor, D.H., Manning, A., Smith, C.L.: The contribution of the minimum wage to us wage inequality over three decades: a reassessment. *Am. Econ. J. Appl. Econ.* **8**(1), 58–99 (2016)
- Barnichon, R., Elsby, M., Hobijn, B., Şahin, A.: Which industries are shifting the beveridge curve? *Month Labor Rev* **135**, 25–37 (2012)
- Baum-Snow, N., Pavan, R.: Understanding the city size wage gap. *Rev. Econ. Stud.* **79**(1), 88–127 (2012)
- Baum-Snow, N., Freedman, M., Pavan, R.: Why has urban inequality increased? *Am. Econ. J. Appl. Econ.* **10**(4), 1–42 (2018)
- Beaudry, P., Doms, M., Lewis, E.: Should the personal computer be considered a technological revolution? Evidence from U.S. metropolitan areas. *J. Polit. Econ.* **118**(5), 988–1036 (2010)
- Beaudry, P., Green, D., Sand, B.: The declining fortunes of the young since 2000. *Am. Econ. Rev. Papers Proc* **104**(5), 381–386 (2014)
- Beaudry, P., Green, D., Sand, B.: The great reversal in the demand for skill and cognitive tasks. *J. Labor Econ.* **34**(S1), 199–247 (2016)
- Bivens, J.: Using standard models to benchmark the costs of globalization for american workers without a college degree. Technical Report 354, Economic Policy Institute (2013)
- Black, D., Kolesnikova, N., Taylor, L.: Earnings functions when wages and prices vary by location. *J. Labor Econ.* **27**(1), 21–47 (2009)
- Black, D.A., Kolesnikova, N., Taylor, L.J.: Local labor markets and the evolution of inequality. *Annu. Rev. Econ.* **6**(1), 605–628 (2014)
- Bound, J., Johnson, G.: Changes in the structure of wages in the 1980s: an evaluation of alternative explanations. *Am. Econ. Rev.* **82**(3), 371–392 (1992)
- Bowles, S.: The production process in a competitive economy: Walrasian, neo-hobbesian, and marxian models. *Am. Econ. Rev.* **75**(1), 16–36 (1985)
- Bowles, S., Gintis, H.: The marxian theory of value and hetero-geneous labour: a critique and reformulation. *Camb. J. Econ.* **1**(2), 173–192 (1977)
- Braverman, H.: *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. Modern Reader Paperbacks. Monthly Review Press, New York (1974)
- Bronfenbrenner, K.: *Uneasy terrain: The impact of capital mobility on workers, wages, and union organizing*. Technical report, United States Trade Deficit Commission (2000)
- Card, D.: The effect of unions on the structure of wages: a longitudinal analysis. *Ind. Labor Relat. Rev.* **54**(2), 296–315 (2001)

- Card, D., DiNardo, J.: Skill-biased technological change and rising wage inequality: some problems and puzzles. *J. Labor Econ.* **20**(4), 733–783 (2001)
- Card, D., Heining, J., Kline, P.: Workplace heterogeneity and the rise of west German wage inequality. *Q. J. Econ.* **128**(3), 967–1015 (2013)
- Card, D., Lemieux, T., Riddell, W.C.: Unions and wage inequality: The roles of gender, skill and public sector employment. NBER Working Papers 25313, National Bureau of Economic Research (2018)
- Ciccone, A., Peri, G.: Long-run substitutability between more and less educated workers: evidence from U.S. states. *Rev. Econ. Stat.* **87**(4), 652–663 (2005)
- Cloutier, N.: Metropolitan income inequality during the 1980s: the impact of urban development, industrial mix, and family structure. *J. Reg. Sci.* **37**(3), 459–478 (1997)
- Davis, S.J., Faberman, R.J., Haltiwanger, J.C.: Recruiting intensity during and after the great recession: national and industry evidence. *Am. Econ. Rev.* **102**(3), 584–88 (2012)
- Diamond, R.: The determinants and welfare implications of us workers' diverging location choices by skill: 1980–2000. *Am. Econ. Rev.* **106**(3), 479–524 (2016)
- Fallick, B., Fleischman, C.A., Rebitzer, J.B.: Job-hopping in silicon valley: some evidence concerning the microfoundations of a high-technology cluster. *Rev. Econ. Stat.* **88**(3), 472–481 (2006)
- Farber, H.S., Herbst, D., Kuziemko, I., Naidu, S.: Unions and inequality over the twentieth century: New evidence from survey data. Technical Report 24587, National Bureau of Economic Research (2020)
- Farrokhi, F., Jinkins, D.: Wage inequality and the location of cities. *J. Urban Econ.* **111**, 76–92 (2019)
- Fortin, N.: Higher education policies and the college wage premium: cross-state evidence from the 1990s. *Am. Econ. Rev.* **96**(4), 959–987 (2006)
- Freeman, R., Kleiner, M.: Employer behavior in the face of union organizing drives. *Ind. Labor Relat. Rev.* **43**(1), 351–365 (1990)
- Gintis, H.: The nature of labor exchange and the theory of capitalist production. *Rev. Radic. Polit. Econ.* **8**(2), 36–54 (1976)
- Giuliano, L., Levine, D.I., Leonard, J.: Manager race and the race of new hires. *J. Labor Econ.* **27**(4), 589–631 (2009)
- Goldin, C., Katz, L.: Long-run changes in the wage structure: narrowing, widening, polarizing. *Brook. Papers Econ. Activity* **2007**(2), 135–165 (2007)
- Goldstein, A.: Revenge of the managers: labor cost-cutting and the paradoxical resurgence of managerialism in the shareholder value era, 1984 to 2001. *Am. Soc. Rev.* **77**(2), 268–294 (2012)
- Goos, M., Manning, A.: Lousy and lovely jobs: the rising polarization of work in Britain. *Rev. Econ. Stat.* **89**(1), 118–133 (2007)
- Gordon, D.M.: Who bosses whom? The intensity of supervision and the discipline of labor. *Am. Econ. Rev.* **80**(2), 28–32 (1990)
- Gordon, D.M.: Bosses of different stripes: a cross-national perspective on monitoring and supervision. *Am. Econ. Rev.* **84**(2), 375–379 (1994)
- Gordon, D.M.: Fat and Mean: The Corporate Squeeze of Working Americans and the Myth of Managerial 'Downsizing'. The Free Press, New York (1996)
- Gould, E.D.: Cities, workers, and wages: a structural analysis of the urban wage premium. *Rev. Econ. Stud.* **74**(2), 477–506 (2007)
- Green, F., McIntosh, S.: Union power, cost of job loss, and workers' effort. *Ind. Labor Relat. Rev.* **51**(3), 363–383 (1998)
- Green, F., Weisskopf, T.E.: The worker discipline effect: a disaggregative analysis. *Rev. Econ. Stat.* **72**(2), 241–249 (1990)
- Gyourko, J., Mayer, C., Sinai, T.: Superstar cities. *Am. Econ. J. Econ. Policy* **5**(4), 167–199 (2013)
- Hershbein, B., Kahn, L.: Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *Am. Econ. Rev.* **108**(7), 1737–72 (2018)
- Heuermann, D., Halfdanarson, B., Suedekum, J.: Human capital externalities and the urban wage premium: two literatures and their interrelations. *Urban Stud.* **47**(4), 749–767 (2010)
- Hirsch, B.T., Macpherson, D.A.: Union membership and coverage database from the current population survey: note. *Ind. Labor Relat. Rev.* **56**(2), 349–354 (2003)
- Howell, D.R., Wolff, E.N.: Trends in the growth and distribution of skills in the U.S. workplace, 1960–1985. *ILR Rev.* **44**(3), 486–502 (1991)
- Howell, D.R., Wolff, E.N.: Technical change and the demand for skills by U.S. industries. *Camb. J. Econ.* **16**(2), 127–146 (1992)
- Hsiao, C.: Analysis of Panel Data, 3rd edn. Cambridge University Press, New York (2014)
- Juhn, C., Murphy, K., Pierce, B.: Wage inequality and the rise in returns to skill. *J. Polit. Econ.* **101**(3), 410–442 (1993)
- Karoly, L., Klerman, J.: Using regional data to reexamine the contribution of demographic and sectoral changes to increasing wage inequality. In: Bergstrand, J.H. (ed.) *The Changing Distribution of Income in an Open U.S. Economy*, pp. 183–216. North-Holland, Amsterdam, The Netherlands (1994)
- Katz, L.: Efficiency wage theories: a partial evaluation. *NBER Macroecon. Annu.* **1**, 235–276 (1986)
- Katz, L., Krueger, A.: The rise and nature of alternative work arrangements in the United States, 1995–2015. *ILR Rev.* **72**(2), 382–416 (2019)
- Katz, L., Murphy, K.: Changes in relative wages: supply and demand factors. *Q. J. Econ.* **107**(1), 35–78 (1992)
- Koeniger, W., Leonardi, M., Nunsia, L.: Labor market institutions and wage inequality. *Ind. Labor Relat. Rev.* **60**(3), 340–356 (2007)
- Krueger, A.: How computers have changed the wage structure: evidence from microdata, 1984–1989. *Q. J. Econ.* **108**(1), 33–60 (1993)
- LaLonde, R.J., Topel, R.H.: Labor market adjustments to increased immigration. In: Abowd, J., Freeman, R. (eds.) *Immigration, Trade, and the Labor Market*, pp. 167–199. University of Chicago Press, Chicago (1991)
- Lee, D.: Wage inequality in the U.S. during the 1980s: Rising dispersion of falling minimum wage? *Q. J. Econ.* **114**, 977–1023 (1999)
- Lemieux, T.: Increasing residual wage inequality: composition effects, noisy data, or rising demand for skill? *Am. Econ. Rev.* **96**(3), 461–498 (2006)
- Leonardi, M.: The effect of product demand on inequality: evidence from the united states and the United Kingdom. *Am. Econ. J. Appl. Econ.* **7**(3), 221–247 (2015)
- Lindley, J., Machin, S.: Spatial changes in labour market inequality. *J. Urban Econ.* **79**, 121–138 (2014)
- Molloy, R., Smith, C.L., Trezzi, R., Wozniak, A.: Understanding declining fluidity in the u.s. labor market. *Brookings Papers on Economic Activity*, 183–237 (2016)
- Moretto, E.: Real wage inequality. *Am. Econ. J. Appl. Econ.* **5**(1), 65–103 (2013)
- Ottaviano, G.I.P., Peri, G.: Rethinking the effect of immigration on wages. *J. Eur. Econ. Assoc.* **10**(1), 152–197 (2012)
- Piketty, T., Saez, E.: The evolution of top incomes: a historical and international perspective. *Am. Econ. Rev.* **96**(2), 200–205 (2006)
- Rebitzer, J.B.: Unemployment, long-term employment relations, and productivity growth. *Rev. Econ. Stat.* **69**(4), 627–635 (1987)
- Ruggles, S., Flood, S., Foster, S., Goeken, R., Pacas, J., Schouweiler, M., Sobek, M.: IPUMS USA: Version 11.0 [dataset] (2021)
- Salvatori, A.: The anatomy of job polarisation in the UK. *J. Labour Mark. Res.* **8**(52), 1–15 (2018)
- Shapiro, C., Stiglitz, J.E.: Equilibrium unemployment as a worker discipline device. *Am. Econ. Rev.* **74**(3), 433–444 (1984)
- Staiger, D., Stock, J.: Instrumental variables regression with weak instruments. *Econometrica* **65**, 557–586 (1997)
- Stainback, K., Tomaskovic-Devey, D.: Intersections of power and privilege: long-term trends in managerial representation. *Am. Soc. Rev.* **74**(5), 800–820 (2009)
- Tinbergen, J.: Substitution of graduate by other labour. *Kyklos* **27**(2), 217–226 (1974)
- Wooldridge, J.: *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge (2002)
- Zicklin, G.: Numerical control machining and the issue of deskilling: an empirical view. *Work and occupations* **14**(3), 452–466 (1987)
- Zimmerman, S.D.: Elite colleges and upward mobility to top jobs and top incomes. *Am. Econ. Rev.* **109**(1), 1–47 (2019)

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.