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Skill-Biased Occupation Growth

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SKILL-BIASED OCCUPATION GROWTH

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Abstract

This paper documents that employment and wage growth of occupations increase monotonically with measures of occupational skill intensity since 1980 in the US, contrary to the popular interpretation of labor market polarization. Skill-biased occupation growth is not driven by a specific gender, age group, decade, or occupation classification. A simple extension of routinization framework which allows for skill heterogeneities within occupations is capable of jointly explaining skill-biased occupation growth and polarization as well as their evolution over time.

KEYWORDS: *Occupations, Skills, Inequality, Technological Change*

JEL Codes: J20, J24, J31, 033

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NON-TECHNICAL SUMMARY

A growing literature documents the pervasiveness of labor market polarization, which refers to slower growth in employment and wages of middle-wage jobs relative to others located at the tails of the wage distribution in the last decades. In spite of the fact that real wage and employment of any given education group has been increasing relative to lower education groups since the 1980s, the literature often interprets polarization in terms of skills, as the manifestation of non-monotonic changes in the demand for skills as opposed to the monotonicity implied by the canonical skill-biased technical change (SBTC) model.

This paper's starting point is the observation that college and noncollege workers exist throughout the occupational wage distribution. Moreover, the ability of occupational wages to reflect skills becomes poorer at the bottom-half of the distribution. These call for a reassessment of occuption growth trends from the lens of skills.

Observing the employment and wage growth patterns of detailed occupations along various dimensions of skills including education, cognitive skill, and training measures, the paper documents that occupations' growth trends in employment and wages are monotonically increasing with skills. The monotonicity of occupation growth trends is not driven by a specific gender, age group, and occupation classification. While skill-biased occupation growth is remarkably stable within each decade until 2010, polarization by wages displays significant qualitative changes across time. In particular, low-tail jobs gradually dominated the polarization by wages, which suggests a mild decline in the slope of skill-biased occupation growth.

Polarization observation motivated a nuanced understanding of SBTC by introducing tasks such that occupations with different task content are heterogeneously affected by the advances in computing technology. The routinization framework proved the importance of differentiating tasks from skills, which are inherently the same in the canonical SBTC model. A common theme in both the standard SBTC and routinization frameworks is the one to one mapping of skills to tasks either absolutely or conditional on the technology. This paper introduces a natural extension of the routine-biased technical change models by introducing skill heterogeneity within occupations. When cognitive skills and noncognitive labor market qualities are allowed to differ, an otherwise standard routine-biased technical change model is able to generate the skill-wage mismatch and thereby explain polarization and skill-biased occupation growth jointly with the forces of routinization.

An indirect implication of allowing skill heterogeneity within occupations is the removal of ad hoc restrictions on the movement of workers across occupations. This feature of the model introduces dynamics on the growing tails of wage distribution that are consistent with changing time patterns of job growth in the US. At the earlier stages of routinization, increasing relative wages of nonroutine workers attracts more high-wage workers than low-wage workers of any skill type into nonroutine occupations, which gradually reverses and leads to the dominance of occupation growth by low-wage jobs of all skill types at later stages of technological progress.

1 Introduction

A growing literature documents the pervasiveness of labor market polarization, which refers to slower growth in employment and wages of middle-wage jobs relative to others located at the tails of the wage distribution in the last decades.[1] In spite of the fact that real wage and employment of any given education group has been increasing relative to lower education groups since the 1980s (Acemoglu and Autor, 2011), the literature often interprets polarization in terms of skills, as the manifestation of non-monotonic changes in the demand for skills as opposed to the monotonicity implied by the canonical skill-biased technical change (SBTC) model (see, e.g., Autor et al., 2006; Goos and Manning, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013).[2]

Behind the skill-based interpretation of polarization lies two assumptions: (i) a given task is performed only by a specific skill type conditional on the state of technology, and (ii) occupational mean wages sufficiently reflect skills. This paper relaxes these assumptions and explores the role of occupational skill heterogeneity by providing a characterization of the evolution of occupational employment and wage structure with respect to differences in observable skill intensities across tasks.[3]

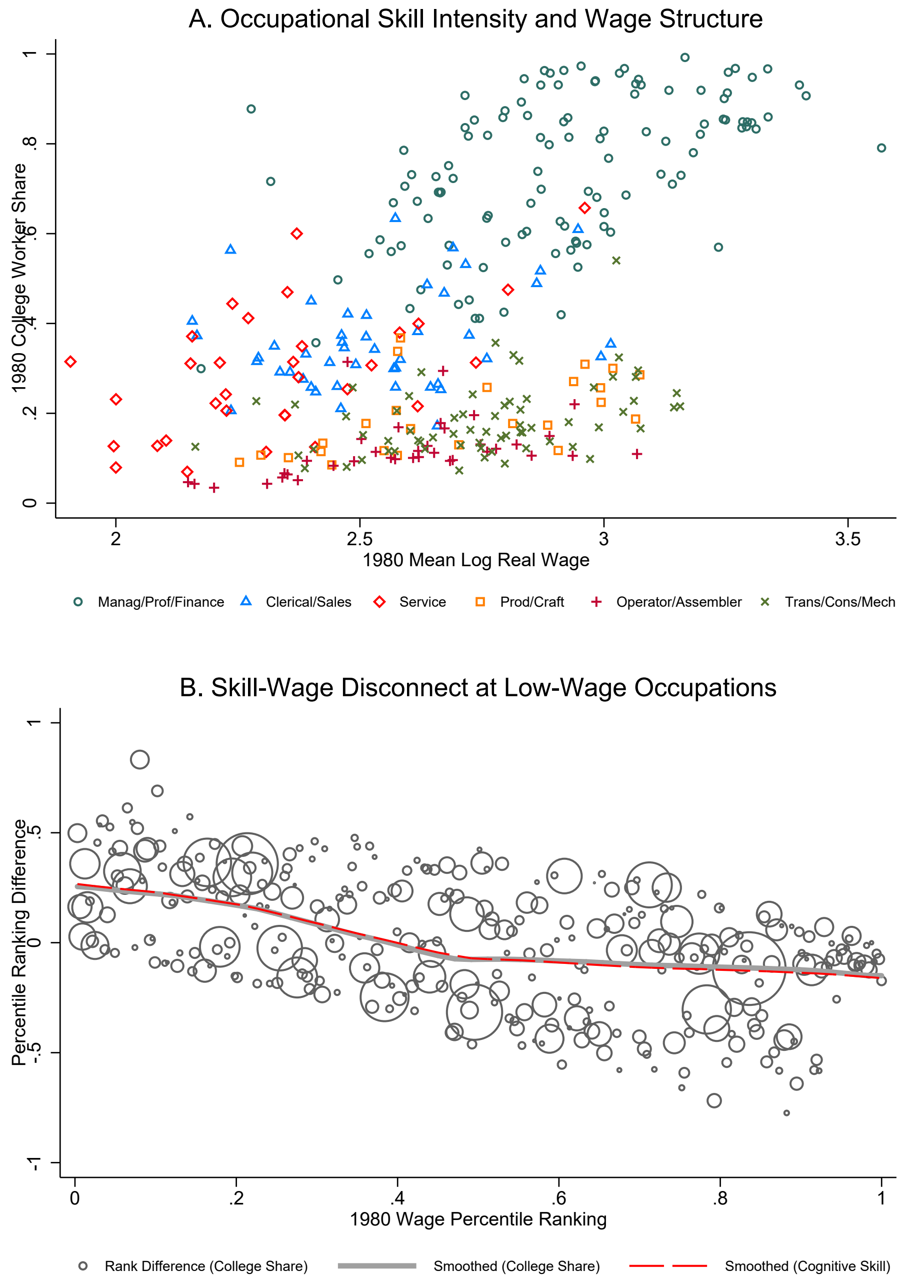
Figure 1 summarizes the reasons for why these simplifying assumptions remain too naive. First, Panel A plots the share of workers above high school education on the left axis against mean log hourly real wages in 1980 for detailed occupations from Census. As the variability of college intensity is high throughout the wage distribution, there is quite substantial weight of college workers even in the low-wage jobs. The share of college workers in total hours of occupations below the median wage has a mean of one fourth already in

[1] Polarization of employment is documented both in the US (Autor et al., 2006, 2008; Autor and Dorn, 2013), the UK (Goos and Manning, 2007), and many other advanced economies (Goos et al., 2009, 2014). Bárány and Siegel (2018) argue that polarization starts as early as the 1950s. There is also evidence for polarization of wages in the US (Autor and Dorn, 2013).

[2] The canonical model provides a simple demand and supply framework of skills and is remarkably useful in understanding the evolution of inequalities throughout the 20th century (Goldin and Katz, 2008). See Acemoglu and Autor (2011) for a comprehensive discussion on the shortcomings of the canonical model.

[3] The existing task literature has taken a revolutionary step in characterizing the structural change of employment by untangling tasks from skills (e.g., Autor et al., 2003) and already noted the skill heterogeneity within occupations (e.g., Goos and Manning, 2007). However, skill-type heterogeneity within occupations is not reflected in most of the task-based models and explanations of inequality trends. A recent exception is Beaudry et al. (2016) who develop a model of two tasks which are jointly produced by high- and low-skill workers.

Figure 1: Skill Heterogeneity and Wages



Panel A shows mean 1980 log real wages for 323 detailed occupations on the horizonal axis and 1980 share of college workers in occupation's employment on the vertical axis. Means are calculated using labor supply weights. Different shapes correspond to one of six major occupation groups. Panel B plots the percentile ranking of occupations based on their 1980 log wages on the horizontal axis versus the difference between 1980 skill and wage percentile rankings on the vertical axis. Skill ranking is based on college worker shares. Bubble sizes reflect 1980 employment share. Solid and dashed curves respectively show the smoothed rank difference by college shares and alternatively occupational AFQT score as a measure of cognitive skill. Smoothing is done by local polynomials using employment weights. See the data section on occupational AFQT scores. Source: 1980 Census and NLSY-1979

1980.[4]

Second, Panel B compares the wage percentile ranking on the horizontal axis with the difference between college share and wage ranking of occupations on the vertical axis. If skill and wage ranking of occupations perfectly overlap, then the ranking difference should be a flat line at zero throughout the wage ranking. However, locally smoothed curves using both college shares and cognitive skill intensity indicate a significantly inverse relationship between wage and skill rankings at the lower half of wage distribution. The figure clearly shows that the bottom wage jobs are paid severely below what is implied by their skill ranking.[5].

How is the changing labor market importance of occupations characterized from the lens of direct measures of skills? I begin answering this question by documenting the employment and wage growth patterns of detailed occupations along various dimensions of skills using education, cognitive skill, and training measures. Documenting the skill-biased occupation growth and establishing its robustness is the main contribution of this paper. I observe that occupations' growth trends in employment and wages are monotonically increasing with skills. The monotonicity of occupation growth trends is not driven by a specific gender, age group, and occupation classification. While skill-biased occupation growth is remarkably stable within each decade until 2010, polarization by wages displays significant qualitative changes across time.[6] It is true that the US labor market has been polarizing, but this paper suggests that it did not evolve into a market dominated by the most and the least skilled workers. In this regard, this paper's empirical contribution bridges the literature on SBTC and labor market polarization by providing a refined skill-based interpretation of occupation growth patterns.

Polarization observation motivated a nuanced understanding of SBTC by introducing tasks such that

[4]In the following decades the share of high-skill workers in low-wage jobs further increased together with the rest of the labor market, reaching just below one half as of 2010.

[5]The broken link between wages and education content at the bottom half of occupational wage distribution is pervasive among all education groups (Appendix Figure A.1). The mismatch is also persistent with residual wages from an individual level regression controlling for demographic characteristics and potential experience (Appendix Figure A.2).

[6]Occupation growth by wages is dominated by the upper tail jobs in the 1980s, U-shaped in the 1990s, and becomes an inverse-J after 2000 (See Autor et al., 2006; Beaudry et al., 2016).

occupations with different task content are heterogeneously affected by the advances in computing technology. The routinization framework starting with Autor et al. (2003) proved the importance of differentiating tasks from skills, which are inherently the same in the canonical SBTC model. A common theme in both the standard SBTC and routinization frameworks is the one to one mapping of skills to tasks either absolutely or conditional on the technology (Autor, 2013). I introduce a natural extension of the routine-biased technical change models by introducing skill heterogeneity within occupations. When skills and labor market qualities are allowed to differ, an otherwise standard routine-biased technical change model is able to generate the skill-wage mismatch and thereby explain polarization and skill-biased occupation growth jointly with the forces of routinization.

An indirect implication of allowing skill heterogeneity within occupations is the removal of ad hoc restrictions on the movement of workers across occupations. This feature of the model introduces dynamics on the growing tails of wage distribution that are consistent with changing time patterns of job growth in the US. At the earlier stages of routinization, increasing relative wages of nonroutine workers attracts more high-wage workers than low-wage workers of any skill type into nonroutine occupations, which gradually reverses and leads to the dominance of occupation growth by low-wage jobs of all skill types at later stages of technological progress. This aspect of the paper is also related to Beaudry et al. (2016) who document the rise of low-wage jobs after 2000 and interpret this as the great reversal of cognitive task demand. While Beaudry et al. (2016) argue the maturity of information technologies as the main driver of the rising share of low-wage workers in nonroutine occupations, I suggest an alternative channel that operates through the interaction of steadily changing technology with non-linear wage schedules across occupations.

The rest of the paper is organized as follows. Section 2 introduces the data. Section 3 documents the skill-biased occupation growth in the US. Section 4 explores the robustness of the trend in temporal and demographic dimensions. Section 5 focuses on the sources of differing disaggregate labor market trends and study an extension of the routine-biased technical change model that offers an inclusive explanation to occupation growth trends. Finally, section 6 concludes.

2 Data

The main unit of analysis throughout this paper is detailed occupations. I classify occupations following Dorn (2009) who develops a consistent and balanced set of occupation codes that allow comparability across 1980, 1990, 2000 Census, and 2005 American Community Survey (ACS). For occupations in 2010 ACS I first transform 2010 *occ* codes to ACS 2005 *occ* equivalents, and then merge according to the crosswalk by Dorn (2009). Excluding farming and fishing occupations, I end up with a balanced panel of 323 occupations.

I use 1980, 1990, 2000 IPUMS Census, and 2010 ACS data for calculating occupational employment shares, real wages, and skill variables based on formal schooling. The measure of employment is annual hours worked which is aggregated to occupations using Census weights. Wages used are hourly and measured as annual real wage income divided by annual hours.[7] I have two main skill variables generated from Census data, mean years of education and share of college workers. In the calculation of all occupational averages observations are weighted by labor supply weights which are calculated as annual hours times population weights.

I complement the Census-based education measures by employing a set of variables reflecting different aspects of skills. From National Longitudinal Survey of Youth (NLSY) 1979 I get The Armed Forces Qualification Test (AFQT) score, which is widely used as a measure of general cognitive skills (Heckman et al., 2006). From 1983 to 1992 the survey reports AFQT scores as well as 3 digit 1980 Census occupation codes. After pooling observations in all years and using the crosswalk by Autor and Dorn (2013) to match occupation classification used in this study, I calculate occupational mean AFQT scores weighted by customized longitudinal weights.

From the occupational network (O*NET) database published by the National Center for O*NET De-

[7] Details on data cleaning and variable construction are provided in Appendix Section A.1.2.

velopment I obtain the occupational Job Zone information which measures the occupation-specific training requirements. I translate the original intervalled variable to months of training using the table provided by O*NET.

The last source of occupational data is Dictionary of Occupational Titles (DOT) 4th edition. I employ general educational development (GED) and specific vocational preparation (SVP) as alternative skill intensity measures. GED for a particular occupation is given by the highest score out of three categories (reasoning, math, language) each of which is computed in a 6 point scale. SVP provides a more job-specific measure which only includes the training (acquired in school, work, military, institutional or vocational environment) in order to achieve the average performance of the tasks required by the occupation. It does not include schooling without vocational content. I use a version of this variable which translates the 9 point scale of the original variable into training time in months. The dataset I utilize reports the mean DOT variables for Census 1980 occupation codes (England and Kilbourne, 1988). I merge 1980 Census occupations to my occupational dataset using 1980 Census labor supply weights and the crosswalk provided by David Dorn.

3 Occupational Skills and Trends in Occupation Growth

3.1 U-Shaped or Monotonic?

In the literature almost all of the evidence on polarization comes from skill percentiles represented by mean or median wages. If the skill-based interpretation of polarization is true then we expect to confirm it using more direct measures for skills too. The key skill classification in the literature on SBTC is based on attainment of college education. Therefore, I simply start reassessing the role of skills in changing labor market inequalities by comparing occupational employment and wage growth patterns when occupations are ranked by mean wages to those ranked according to college worker intensity. Two alternative variables capture the skill intensity. The first one, college worker share, is the ratio of employment of workers with any college education to the occupation's total employment. The second, college graduate share, is the intensity of workers with at least a college degree in occupation's employment.

Figure 2 presents the growth pattern of occupation employment and wages based on the three alternative measures of occupational skill. Panel A and Panel B plot the smoothed employment share changes and real hourly wage growth by the skill percentiles in the 1980 US labor market, respectively. Circles in the figure correspond to changes by wage percentiles and confirm the polarization for the US between 1980 and 2010 in both of the occupation growth measures. Comparison with Autor and Dorn (2013) who report a similar figure for 1980-2005 period reveals that the last half of the 2000s did not impose a significant change in the long-run polarization outlook.

In the same figure the evolution of occupational employment share and real wages can also be tracked when skill percentiles are formed by high-skill intensity variables. Both relative employment and wage growth of occupations follow monotonic paths along skill percentiles, which strikingly contrast with the U-shaped growth suggested by wage percentiles. A further remark from the figure is that the trend in occupation growth is almost identical according to both high-skill intensity variables.

3.2 Choice of Skill Measure

College worker or college graduate share of employment are relevant metrics for skill intensity from the viewpoint of SBTC hypothesis, but there are other direct measures of skill intensity to check the external validity of the observations in Figure 2. Investigating the robustness of the monotonicity observation with other skill measures can also help understanding the contrasting patterns.

There are reasonable grounds to ask whether other skill measures beyond college shares also align with monotonic demand shift towards more skill-intensive occupations. College worker share is an imperfect measure for education intensity. One concern is that the skill quality in the lower parts of wage distribution

Figure 2: Trends in Employment and Wage Growth

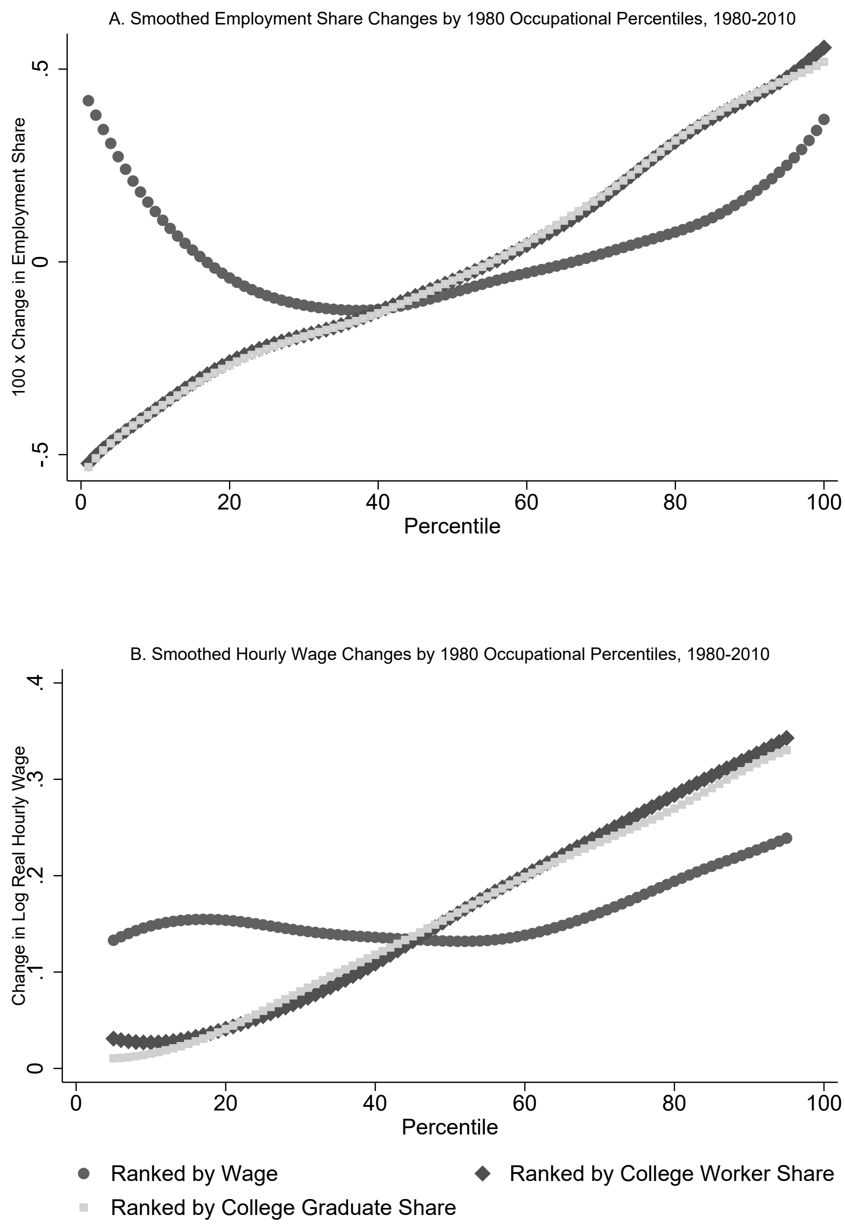


Figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages computed for each employment percentile ranked according to 1980 occupational mean high-skill worker intensity or wages of 323 consistent non-farm occupations following Dorn (2009)'s classification. Construction of employment percentiles, computation of mean wages in each percentile and smoothing procedure follow Autor and Dorn (2013). The data come from 1980 Census and 2010 American Community Survey. College worker share is the ratio of annual hours by workers with at least some college education in occupation's total labor supply. College graduate share is the ratio of annual hours by workers with at least a college degree in occupation's total labor supply. Real wages are calculated as total labor income divided by total hours and adjusted using personal consumption expenditure index. Labor supply weights are used in the computation of education and wages at occupation level.

is low because of the high share of dropouts so that the college intensity variables do not sense the difference between a high school graduate working in a middling job and a worker in the lowest-paid job with just a few years of schooling. Therefore I use mean years of education as an alternative measure.

While education variables measure the intensity of formal schooling they fail to perfectly quantify skills in the broad sense. First, there is unobserved heterogeneity in the quality of education, and the quality of workers is directly reflected into average wages. Therefore wages could measure the skill intensity of an occupation better than education variables. This concern is addressed in the analysis by introducing the AFQT scores for each occupation. Assuming that workers with high AFQT represent better qualities in the market and more likely to end up in better-paid jobs, using this measure sheds light on whether poorly reflected quality by education variables is the main driver of contrasting occupation growth patterns.

The second concern on the education measures of Census is that they could mask the level of education *required* to perform the job. A low-wage occupation may employ workers seemingly as skilled as in the middle-pay one, but if the required level of skills is lower in the low-wage job for the same level of skill compared to middle-wage one, then observed skill intensity again overestimates the true ability proxied by wages. The middle-wage occupations can also look artificially less skill-intensive if they require education or training on the job while low wage jobs do not.

I employ three measures to address education or training beyond schooling. The first is GED variable from DOT. It measures the formal and informal aspects of education that shapes the worker's ability in several dimensions to perform the task. It is a measure of training requirement that involves general skills including but not limited to formal education. The other two focus on the required occupation-specific training from two different sources introduced in the data section: SVP from DOT and Job Zone information from O*NET. The former is indicated as Training (DOT) and the latter as Training (O*NET) in the following tables.

The visual evidence presented in the preceding discussion is clear and shares a common methodology to similar studies on labor market polarization. However, construction of percentiles and the smoothing procedure can potentially exaggerate the difference between results by wage and college intensity rankings.

Table 1: Statistical Tests on the Shape of Occupation Growth by Skills

Panel A. Δ Emp. Shr.	Wage	College Share	Years of Education	AFQT	GED	Training (DOT)	Training (O*NET)
Linear term (alone)	0.754 (+)	0.000 (+)	0.000 (+)	0.003 (+)	0.003 (+)	0.131 (+)	0.000 (+)
Quadratic term	0.004	0.576	0.574	0.186	0.212	0.567	0.299
Suggested shape	$\cup$	$\cup$	$\cup$	$\cup$	$\cup$	$\cup$	$\cap$
Extreme value in the range?	YES	NO	NO	YES	YES	YES	YES
Quadratic shape test	0.003	-	-	0.194	0.258	0.496	0.445
Panel B. Δ Log Wage							
Linear term (alone)	0.074 (+)	0.000 (+)	0.000 (+)	0.000 (+)	0.000 (+)	0.000 (+)	0.000 (+)
Quadratic term	0.005	0.005	0.049	0.910	0.682	0.93	0.002
Suggested shape	$\cup$	$\cap$	$\cap$	$\cap$	$\cap$	$\cap$	$\cap$
Extreme value? in the range?	YES	YES	YES	NO	NO	NO	YES
Quadratic shape test	0.008	0.170	0.303	-	-	-	0.151

Numerals show p-values. The dependent variable in Panel A (B) is the 1980-2010 change in employment share (log of real wages) of occupations. First rows of each panel are based on estimation of linear equation. The sign of the linear term is reported in parentheses. Second rows are based on estimation of the quadratic form. Third rows indicate whether the quadratic specification estimates suggest a convex ($\bigcup$) or a concave ($\bigcap$) relationship. Fourth rows indicate whether the estimated extreme value from quadratic specification ($\frac{-\hat{\gamma_1}}{2\hat{\gamma_2}}$) is inside the range of variables. Fifth row reports the p-value of the null hypothesis that the true relationship is not the suggested one. The table does not report the p-value of the shape test when the extreme value falls outside the range of skill variable. All regressions are estimated using 1980 employment weights and robust standard errors.

I test the hypotheses whether occupation growth in employment and wages fit better to a U-shaped or linear relationship with respect to skill measures with regressions in the spirit of Goos and Manning (2007).

In particular, I estimate the following for testing the U-shape:

$$\Delta d_j = \gamma_0 + \gamma_1 s_j + \gamma_2 s_j^2, \tag{1}$$

where Δd_j denotes occupation j's change in employment share or log real hourly wage over 1980-2010 period and s_j denotes the occupational skill measure. Alternatively, for testing the linear relationship I simply estimate equation (1) when $\gamma_2 = 0$.

Table 1 summarizes the statistically sufficient information regarding the hypothesized shape of 1980-2010 employment share change (Panel A) and log real wage change (Panel B) with respect to skill variables in each column. The first row of each panel shows the p-value associated with the t-test for the significance of the linear term of the corresponding skill measure when there is no quadratic term. The sign of the linear term is reported in parentheses. The second row shows the p-value associated with the coefficient of squared skill measure under quadratic specification. The third row indicates the suggested shape according to the coefficients of quadratic specification.[8]

In both panels the linear specification for wages estimates positive and insignificant coefficients at 5 percent level whereas the quadratic term is statistically significant and confirms the U-shaped relationship. For other skill variables, the linear coefficients are positive and significant except one case. The quadratic term is only significant for O*NET training variable when the dependent variable is wage growth, yet suggesting a hump-shape. Interestingly all of the remaining skill variables indicate hump-shaped relationship in Panel B.

One problem with comparing the estimates of linear and quadratic specifications alone is the lack of statistical significance regarding the hypothesized form of the relationship. For instance, significant quadratic term can also be estimated even when the true form is monotonic and convex. If the U-shaped (hump-shaped) relationship represents the data well, the minimum (maximum) point should not be outside the range of observations. Therefore I report in the forth rows whether the estimated extreme value from quadratic specification ($\frac{-\hat{\gamma_1}}{2\hat{\gamma_2}}$) is inside the range of corresponding skill variable. Wages pass this test as well as the training variable of O*NET in Panel B. Even when the extreme value falls inside the range it could lead to erroneous rejection of the absence of a U-shaped relationship. Lind and Mehlum (2010) develop a formal test on the hypothesis that the quadratic form is the true one.[9] Last rows in both panels report the

[8]Appedix Table A.1 and Table A.2 report the regression results on coefficients, robust standard errors, and R^2 of each specification for all skill variables.

[9]Formally, the null hypothesis is "$\gamma_1 + 2\gamma_2 s_j^l \geq 0$ and/or $\gamma_1 + 2\gamma_2 s_j^h \leq 0$" for the U-shape, where s_j^l and s_j^h are the minimum and maximum values of the skill variable. Testing for the hump-shape requires opposite signs in the null hypothesis.

p-values associated with this test. The conclusion from Table 1 is that occupation growth over the long-run is significantly U-shaped only with wages. The set of direct skill variables confirm skill-biased occupation growth.

4 Growth Patterns by Decade and Demographic Groups

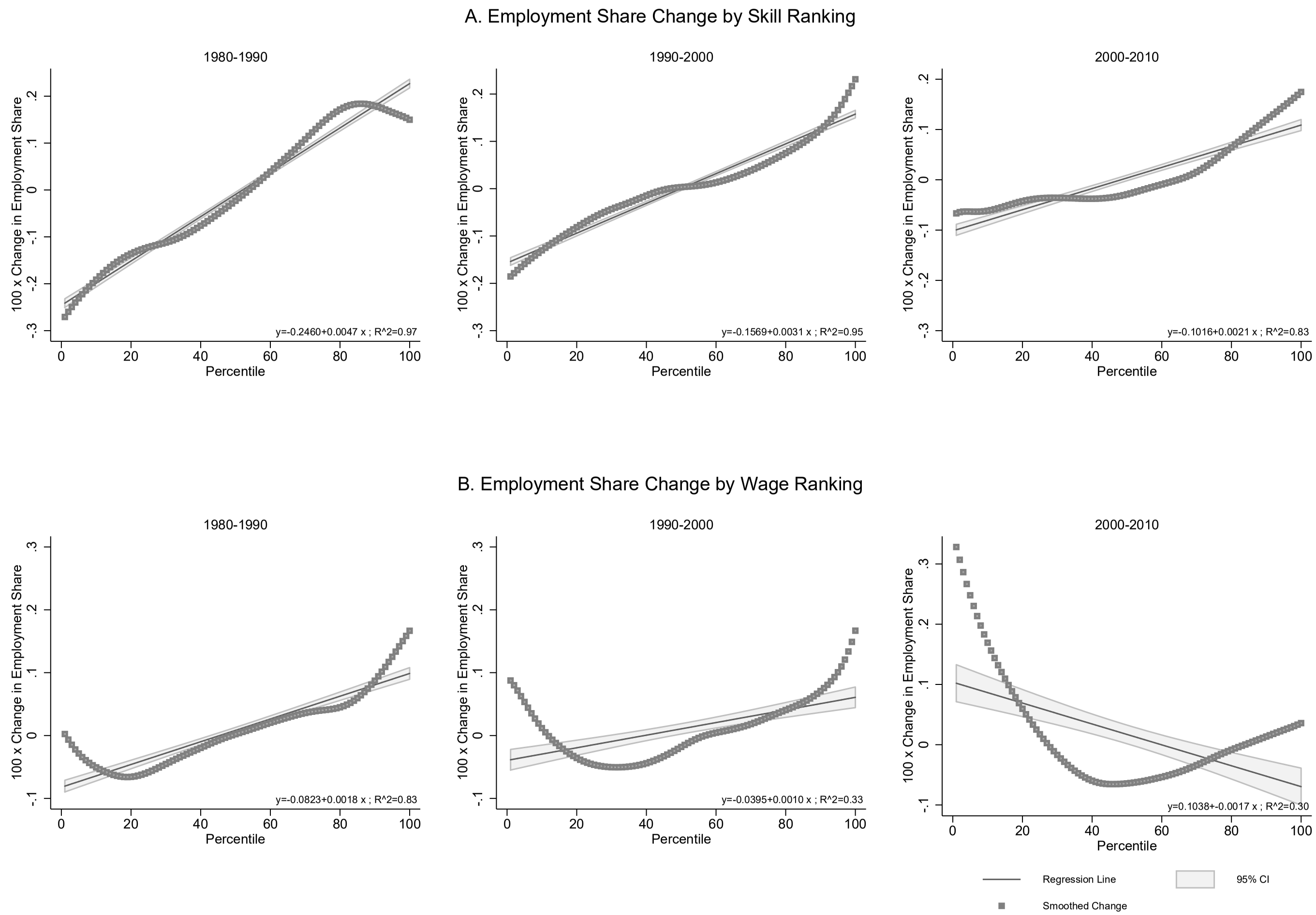
4.1 Growth Patterns by Decade

SBTC hypothesis predicts continuously increasing demand for the more educated worker. In fact estimation of the college wage premium is consistent with this view throughout the 20th century (Goldin and Katz, 2008). If relative demand changes at occupation level also move in a similar way, then monotonic growth pattern should also hold in smaller frames of time. Panel A of Figure 3 plots the tendency of employment share changes in each decade from 1980 to 2010 by skill percentiles according to the mean college share in 1980. Overall, the continuity of skill-biased occupation employment and wage growth is confirmed for each decade after 1980.[10] Appendix Figure A.6 confirms the temporal robustness of skill-biased growth also in wages.

Decadal patterns provide interesting observations regarding the evolution of occupational change. There is a fall in the strength of linearity of the employment growth after 2000, which can be seen by comparing smoothed changes with their linear fit in Figure 3. Also both the coefficient of each skill percentile and the R^2 decrease in each following decade. This can be considered in connection with Beaudry et al. (2016) who document a relative slow-down in the growth of highest-wage jobs. Maturity of organizational capital after 2000 followed by the expansion period in the previous decade is argued as the source of weaker growth in cognitive tasks.

[10]Two related papers (Autor et al., 2006, 2008) observe polarization according to both wage and years of education percentiles during 1990s, which contrasts with the evidence provided here. After showing the robustness of long-run monotonicity by occupation classification in Appendix Section A.2.1, in Section A.2.2 I argue that the contrasting results for the 1990s stem mainly from the choice of occupational classification.

Figure 3: Decadal Trends in Employment Growth



Panel A shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in employment share of occupations ranked by 1980 share of college workers in occupations' employment. Panel B shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in employment share of occupations ranked by 1980 mean log wages. Square points represent the smoothed points. The solid line represents the linear fit of smoothed points with 95 percent confidence interval indicated as shaded areas. The equation shows the OLS coefficients and R^2 from the regression of smoothed points on skill percentiles. Construction of employment percentiles and smoothing procedure follow Autor and Dorn (2013).

In fact, the weakening of high-wage occupation growth compared to the lower part of wage distribution is an evolving phenomenon going back to 1980s. Panel B of Figure 3 shows the occupation growth pattern when ranked by wages in the three decades following 1980. The 1980s polarization outlook is dominated by the upper tail growth, then becomes U-shaped during the 1990s and finally inverse J-shaped after 2000. However, the persistence of monotonicity in job growth in Panel A and the strong linear wage growth after 2000 in Appendix Figure A.6 suggest that the relatively slower growth for some of the high-wage cognitive jobs is not powerful enough to eliminate overall skill-biased occupation growth.

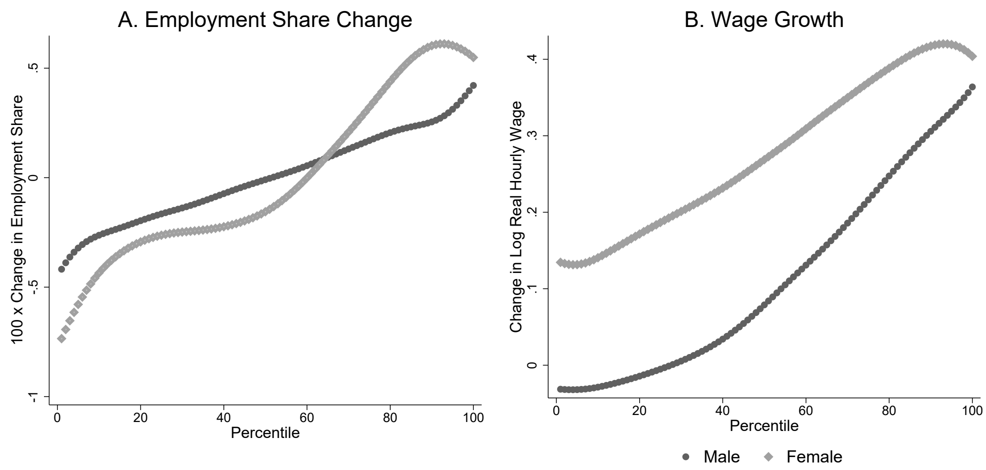
The decade-by-decade analysis by occupational wage and skill produces interesting patterns of inequality. While occupation growth in each decade can be characterized as skill-biased, the U-Shaped polarization observation is the result of a continuous process in which the initial dominance of high-wage job growth gradually translates into higher lower tail growth.

4.2 Occupation Growth in Gender Groups

The literature provides plentiful evidence that the aggregate demand for skilled workers increases regardless of gender. Therefore, it could be expected that the monotonic growth pattern also holds within gender groups. On the other hand, recent papers argue that growth trends in the disaggregate sections of the economy has been affected by female workers (e.g., Ngai and Petrongolo, 2017; Cerina et al., 2017). In order to see if the occupation growth with respect to skills differs by gender, Figure 4 plots smoothed changes by college share of employment when the labor market is split by gender. Both employment and wage growth clearly indicate that the monotonic wage and employment changes take place within both gender groups.

The figure provides additional insights regarding the evolution of gender gaps. In Panel A, employment share of occupations at the upper half of skill distribution increases for both genders at the expense of jobs with lower skill intensity. The shift towards higher skilled occupations is sharper in female employment suggesting that female workers are increasingly represented in skill intensive jobs. While wage growth by

Figure 4: Monotonic Occupation Growth by Gender



The figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment separately by labor markets of males and females.

gender shown in Panel B is in line with the key observation in this study, it is also possible to track the narrowing gender wage gap from the figure. The change in women's occupational wages tend to be above men. At the same time, wage growth in both gender tend to converge towards higher occupational skill intensity.

Both panels therefore imply the previously documented slowdown in the narrowing wage gap after 1980s from a different perspective: women are disproportionately allocated into higher skilled jobs where their wage growth is more similar to men.[11] The implication of this from the occupational perspective is that women are improving the quality of their representation in the labor market which simultaneously comes with a slowdown in the closing rate of gender wage gap.[12]

4.3 Occupation Growth in Age Groups

The behavior of age groups is potentially related to the growth patterns of occupation employment and wages for a number of reasons. First, the demographic structure of the US labor market is significantly

[11] Among others see Blau and Kahn (2006) for the narrowing of the wage gap and slowing down after 1980s and Goldin et al. (2006) for the disappearance of the gender college gap in the US.

[12] Goldin (2014) documents that convexity in hourly earnings with respect to working hours plays a role in the slowdown. The famous examples of jobs characterized by wage-hours convexity are among the ones of highest skill intensity.

affected by the baby-boom cycle. Following the initial decline, the post-1980 period witnessed a sharp increase in the relative supply of experience in both high- and low-skilled labor market (Caselli, 2015). A possible implication is that older workers in the economy can drive occupation employment growth in the skill-intensive occupations if they have a comparative advantage in these jobs. Furthermore, if there is experience-biased technical change then also the wages in these jobs may contribute to the relative wage growth.[13] If this channel is strong enough to drive monotonicity in the entire labor market, then upper tail growth should be dominated by relatively older age groups.

Second, occupational reallocation of employment is potentially associated with the changing age-structure of occupations. In particular, Autor and Dorn (2009) observe that routine-intensive occupations have been getting older. As a result, other occupations might have been growing solely on the shoulders of younger workers flowing out of the routine-intensive jobs. It would be consistent with this argument to observe that the monotonic growth by skills is driven by employment of relatively younger groups.

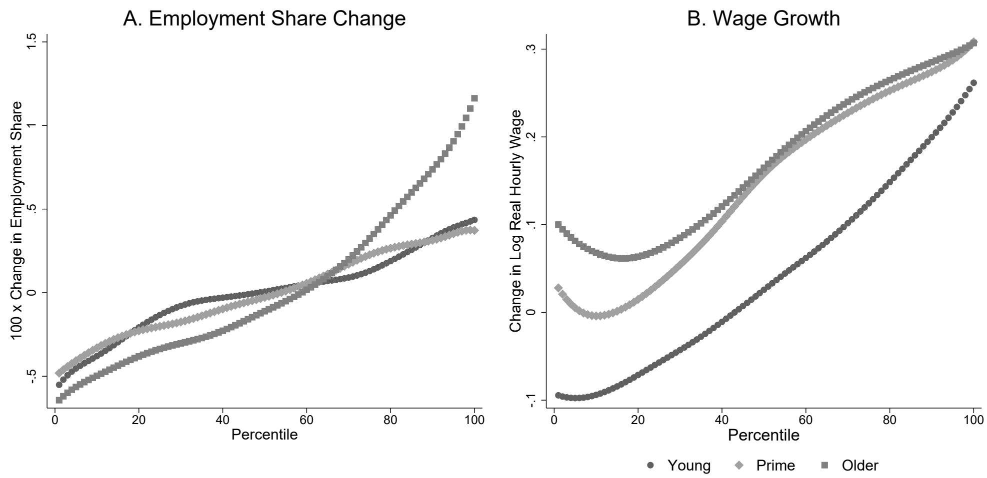
In order to address age-related concerns on the key observation of the paper, I plot smoothed occupation growth of employment share and wages for three age groups in Figure 5. Panel A shows employment share change by skills. As opposed to the first concern, the upper tail growth is not particularly confined to older age groups. On the contrary, the employment share growth for the young-age group is significantly higher above the 80th percentile. In contrast to the second concern, it does not seem that young workers play a special role in employment share changes as they evolve very similarly throughout most of the skill distribution.[14]

Panel B presents the occupational wage growth by skills with respect to the three age groups. The figure suggests evidence in favor of the experience-biased technical change as the wage growth tends to be higher for older groups. Aggregate pattern observed in wage growth by skills is also not particularly driven by any

[13] The term is introduced by Caselli (2015).

[14] The exception is for occupations of highest skills. However, this is not predicted by the routine-biased technical change model, where workers that are employed (or can potentially work) in routine-intensive jobs are reallocated in the low-wage services occupations (Autor and Dorn, 2013).

Figure 5: Monotonic Occupation Growth by Age



The figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment separately by labor markets of age groups. Young, prime, and older groups correspond to workers of age 16-29, 30-54, and 55-64.

of the groups. The only violation to monotonicity is seen for prime age and older groups confined to the last 5 percentile of employment. Moreover, the size of twist at the bottom of distribution is limited in size.[15]

In sum, the evidence across time and demographic groups suggests that occupation growth in favor of relatively skilled occupations is a pervasive fact of the US labor market.

5 An Inclusive Approach to Occupational Growth Trends

The primary reason behind different occupation growth patterns is the skill-wage mismatch observed in Figure 1. The aim of this section is to build insights on how to make sense of the seemingly contrasting inequality trends. I first develop more evidence on the failure of available measures of occupational skills in predicting the ranking of occupations by wages around the 1980s and provide suggestive evidence that task-specific conditions do a better job than skills in understanding the wage hierarchy particularly at the lower half of the wage distribution. Second, in order to theoretically address the root cause of different occupational growth patterns, I introduce a simple extension of the routine-biased technical change model

[15] Quadratic polynomial fit of wage changes by prime and older groups are not statistically different from the linear fit.

of Autor et al. (2003), which differentiates market quality of workers and their cognitive skills and is capable of explaining both skill-biased and polarizing occupation growth patterns as well as their evolution over time.

5.1 More Evidence on the Occupational Skill-Wage Disconnect

Why do we observe polarization by wages but not by other skill measures? The answer partially lies in the strength of the connection between wages and direct skill measures for low and high wage jobs, on which Figure 1 provides an early insight: occupational wages in 1980 reflect skills well for the upper half of wage distribution, whereas the occupations' pay structure in the lower part is different than what is predicted by their skill intensity. This is important in skill-based interpretation of polarization since occupational wages are treated as a one dimensional index of skills (Goos and Manning, 2007).

I start with complementary direct evidence to Figure 1. The disconnect between occupational skill mismatch is not pertained only to college worker intensity. Appendix Figure A.1 shows that the mismatch between occupational wages and education intensity is observed among all education groups. The long tradition of Mincerian wage regressions suggest that individual experience, gender and ethnic background have significant wage effects, which could lead to the observed disconnect in the comparison of raw occupational averages. Appendix Figure A.2 suggests that it is also persistent when residual wages from a regression of individual wages controlling for demographic characteristics and potential experience are used.

The rest of this subsection discusses that the disconnect between the wage and skill structure among the lower paid half of occupations is common to different aspects of skills. I present in Table 2 the partial correlates of wages in both halves of wage distribution using the set of occupational skill measures introduced above. To enable comparison across specifications by different skill variables I use the percentile rank of variables in regressions. For all different skill variables wages correlate well with skills for the upper half of wage distribution (Panel B) and the association is weaker and mostly insignificant for the lower half (Panel

Table 2: Predicting Occupational Skills with Wages, 1980

(Dependent Variable: Percentile Ranking of Occupational Skill Measures)

A. Lower Half of 1980 Wage Distribution

	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (ONET)
Wage Percentile Rank	-0.02	0.04	-0.05	0.13	0.38	0.27
	(0.19)	(0.20)	(0.17)	(0.22)	(0.25)	(0.16)
Constant	0.36	0.35	0.38	0.30	0.17	0.37
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Observations	161	161	161	161	161	161
R^2	0.00	0.00	0.00	0.01	0.08	0.05

B. Upper Half of 1980 Wage Distribution

	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (ONET)
Wage Percentile Rank	0.65	0.68	0.66	0.59	0.86	0.51
	(0.21)	(0.19)	(0.17)	(0.15)	(0.14)	(0.15)
Constant	0.17	0.14	0.14	0.23	0.00	0.31
	(0.17)	(0.16)	(0.14)	(0.12)	(0.11)	(0.12)
Observations	162	162	162	162	162	162
R^2	0.11	0.13	0.14	0.14	0.22	0.11

Table shows the coefficients estimated by OLS from the regression of occupational percentile rank of corresponding skill measure in columns on percentile rank of average occupational wage in 1980. Panel A (B) shows the results for occupations below (above) the median of 1980 mean wage distribution. Wages, years of schooling and college share are computed from 1980 Census. See data section in the main text for skill variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses.

A).[16] Additional observations can be made from the table. First, the reported coefficients are small and insignificant for the lower half of wage distribution and the R^2s are relatively too low. Second, training variables have a higher coefficient compared to education variables and AFQT in low wage occupations which implies that occupation/firm-specific training possibly has more weight in occupational wage determination. However the breaking link between wage and skill structure is clear.[17]

Next, I propose some occupation-specific attributes that has the potential explain the sorting of occupational wages. Task complexity could reflect marketable skills that are not captured by the observable skill measures. In Table 3 the percentile ranking of task characteristics are regressed on wage percentile

[16] The only exception for significance is training measure from O*NET which is statistically significant only at 10 percent level.

[17] The weakening wage-skill relationship at the lower half of wage distribution persists net of demographic and locational effects. Table 3 replicated by residual wages from individual-level wage regressions including controls for age, gender, race and urban status yield similar results and is available upon request.

Table 3: Predicting Occupational Tasks with Wages, 1980

(Dependent Variable: Percentile Ranking of Occupational Task Measures)

	Abstract	Manual	Routine	Time Demand	Cognitive Demand	Hazard
A. Lower Half of 1980 Wage Distribution						
Wage Percentile Rank	0.14	0.48	0.12	0.59	0.86	0.64
	(0.25)	(0.34)	(0.34)	(0.16)	(0.16)	(0.16)
Constant	0.31	0.36	0.50	0.23	0.11	0.29
	(0.05)	(0.10)	(0.10)	(0.05)	(0.04)	(0.06)
Observations	161	161	161	161	161	161
R^2	0.01	0.06	0.00	0.16	0.33	0.14
B. Upper Half of 1980 Wage Distribution						
	Abstract	Manual	Routine	Time Demand	Cognitive Demand	Hazard
Wage Percentile Rank	0.86	-0.27	-0.56	0.81	0.65	-0.63
	(0.15)	(0.23)	(0.30)	(0.20)	(0.15)	(0.20)
Constant	0.07	0.68	0.84	0.03	0.25	0.96
	(0.11)	(0.18)	(0.23)	(0.15)	(0.11)	(0.15)
Observations	162	162	162	162	162	162
R^2	0.24	0.02	0.05	0.18	0.16	0.08

Table shows the coefficients estimated by OLS from the regression of occupational percentile rank of corresponding task measure in columns on percentile rank of 1980 average occupational wage. Panel A (B) shows the results for occupations below (above) the median of 1980 mean wage distribution. Wages, years of schooling and college share are computed from 1980 Census. See data section in the Appendix for task variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses.

ranking. As the natural starting point, I first focus on the tasks suggested by Autor and Dorn (2013). First three columns show the association of three task aspects in Autor and Dorn (2013) with wages in the upper and lower half of occupational wage structure. Abstract, routine, and manual tasks seem to have higher coefficients compared to direct skill measures, but are insignificant.

Another dimension of task complexity can be motivated by the compensating wage differentials literature (Rosen, 1974, 1986). In this view wages are higher if a job requires a less desired task performance requirement, e.g. it is more difficult, riskier and demanding. In discussing the recent persistence in the gender gap, Goldin (2014), in a compensating differentials framework, explains why workers with higher individual costs of supplying longer hours choose to work in low-wage jobs. In the last three columns of Table 3 I introduce three additional task measures to quantify how demanding a job is based on the ILO's definition of working conditions. The first measure is on the time demand of the job proxied by the O*NET work context variable “Duration of Typical Work Week”. The second one is a measure of cognitive demands of the job. I proxy this aspect by O*NET work activity variable “Analyzing Data or Information”. The last one measures the hazard involved in the performance of a job by a combination of O*NET variables introduced in the data section of the appendix. These three capture the opportunity cost of leisure, the cost of mental effort, and the riskiness of the task, all of which are potentially related to wellbeing of the worker and often dictated by the working conditions. In Table 3 all of the alternative task complexity measures correlate well with wages in the lower half.

These observations clearly imply that any conceptual framework that maps occupational wages only to measurable cognitive skill intensities like those employed in this paper has to underestimate the worker skills embedded in the low-pay jobs at the cost of missing a part of the skill-biased nature of technical change (e.g., Acemoglu and Autor, 2011; Autor and Dorn, 2013). Similarly, models such as the canonical SBTC that ignore the occupational wage structure and only focus on worker skills cannot predict the remarkable trends in occupational inequality. In the following, I show that allowing for skill heterogeneities in the routine-biased technical change model is rich enough to address all aspects of skill- and occupation-based inequalities.

5.2 Skill and Task Heterogeneity in a Model of Routinization

The model distinguishes measurable (cognitive) skills and unmeasurable labor market quality that are potentially non-cognitive. Labor market quality is independent from cognitive skills and can stem from the interaction of individual-specific attributes and occupation-specific production processes (Goldin, 2014). A possible interpretation based on the suggestive evidence in the preceding discussion is that some workers are more able in dealing with more complex/difficult tasks better than others. In addition, the model defines heterogeneity in cognitive skills in terms of two skill types. This extends the existing routine-biased technical change models so that college and noncollege workers could be jointly present in any occupation.

Workers can choose among two types of tasks, routine and nonroutine, which offer a single wage schedule in routine tasks, and two in nonroutine corresponding to high-wage and low-wage occupations.

There are two types of tasks, routine and nonroutine following the framework of Autor et al. (2003). The representative firm operates through the following constant elasticity of substitution production function:

$$Y = \left((A_r R)^{\epsilon} + (A_n N)^{\epsilon}\right)^{\frac{1}{\epsilon}}, \tag{2}$$

where Y is the final output, $\epsilon < 1$ and $\frac{1}{1-\epsilon}$ is the elasticity of substitution across tasks, A_i such that $i \in \{r, n\}$ is the technology of routine (r) or nonroutine (n) task which can exogenously grow, R and N are the supply of routine and nonroutine workers in efficiency units. The firm chooses routine and nonroutine efficiency labor to maximize profits taking the output price as numeraire and task wages w_r and w_n as given.

There are two types of workers whose supply is exogenously given as in the canonical model of SBTC (e.g., Katz and Murphy, 1992). Total mass of high-skill workers is k and the mass of low-skill workers is normalized to 1. High- and low-skill workers are perfect substitutes in the production of both routine and nonroutine tasks. Workers in each type of skill are endowed with quality, θ, independently drawn from the same type of continuous distribution. F_S and F_U denote the cumulative distribution functions of high and low types. The only difference between high- and low-skill workers with the same quality draw is that the former is $h > 1$ times more productive than the latter.

I consider the simplest case for the distribution of worker quality in order to obtain tractable analytical solutions. Worker quality for each skill type is independently drawn from continuous uniform distribution on the interval $[0, 1]$, i.e., $F_S(\theta) = F_U(\theta) = \theta$.

Nonroutine task production offers two types of technology. One involves higher return to worker quality but only pays non-negative wages to workers of quality that is higher than a threshold value, while the other is open to all workers but offers a low compensation schedule. This feature of the model enables the existence of high- and low-wage nonroutine jobs.[18] I assume linear schedules where occupational differences are introduced by occupation-specific slope and intercept constants, denoted by a and c below. The efficiency of the worker with quality θ and skill-level s_j such that $j = \{S, U\}$ is $b_{1j}(\theta) = a_1 s_j \theta + c_1$ when working in the low-wage nonroutine job; $b_{2j}(\theta) = a_2 s_j \theta$ when in routine job; $b_{3j}(\theta) = a_3 s_j \theta - c_3$ when in high-wage nonroutine job, where $s_S = h$, $s_U = 1$.[19] Hence, the worker is paid $w_n b_{1j}(\theta)$, $w_r b_{2j}(\theta)$, $w_n b_{3j}(\theta)$ in low-wage nonroutine, routine, and high-wage nonroutine occupations, respectively.

The worker assignment to occupations of low-skill workers is illustrated in Figure 6. The vertical axis shows the wage schedule offered by each occupation relative to nonroutine task wage by market quality on the horizontal axis. Low-wage nonroutine occupations require simple tasks such that even a worker with zero market quality can operate with positive productivity. Assuming that the relative task wages are given by $\frac{{w_r}^0}{{w_n}^0}$, the low-wage nonroutine wage is greater than other occupations as long as the market quality is less than ${\overline{\theta}_L}^0$ in the figure. Complex tasks require a certain level of market quality to yield positive productivity and allow higher return to quality. For instance, a worker who is unable to provide market work for long hours produces a real loss as a surgeon, while the efficiency structure assumes that surgeons of marginally higher quality earn relatively higher wages compared to less complex occupations. In the figure, workers with quality greater than ${\overline{\theta}_H}^0$ are paid the highest wage in the high-wage nonroutine occupations. Routine tasks are somewhere in between the simple and complex tasks in terms of productivity. Consequently, relative routine wages outperform others for workers of market quality between ${\overline{\theta}_L}^0$ and ${\overline{\theta}_H}^0$.

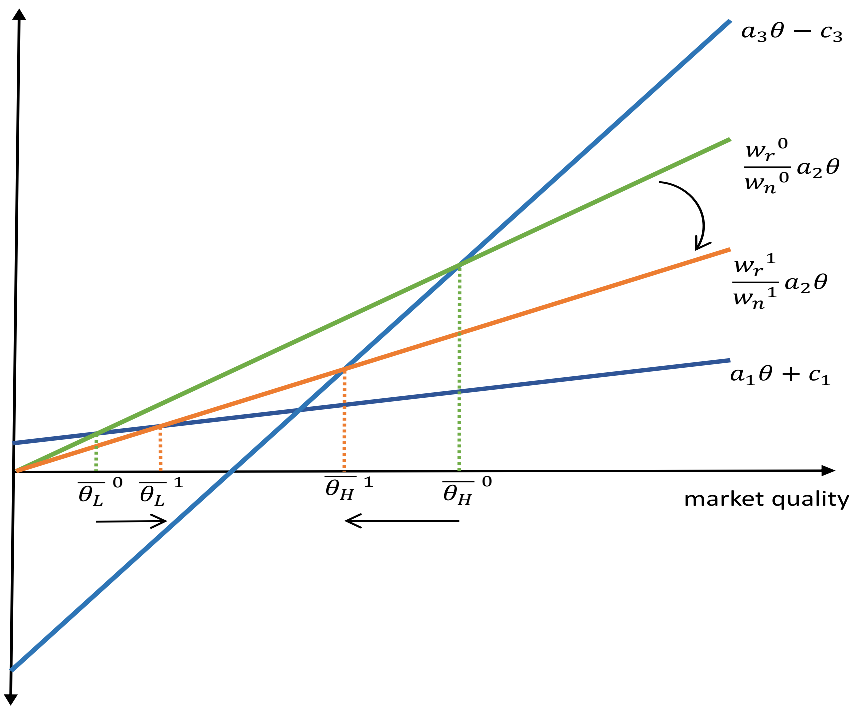
It can be shown that when $a_1 + c_1 < \frac{w_r}{w_n} a_2 < a_3 - c_3$, the efficiency schedules above satisfy log-supermodularity and workers are sorted based on their quality draws (Costinot and Vogel, 2010).[20] In particular, there exist two cut-offs for low-skill worker, $0 < \overline{\theta}_L < \overline{\theta}_H < 1$, such that below $\overline{\theta}_L$ worker

[18] For simplicity, the two occupations performing nonroutine tasks are introduced as perfect substitutes.

[19] I also assume that all slope and intercept coefficients of the efficiency schemes are non-negative.

[20] When $\frac{w_r}{w_n} a_2 > a_3$ then the set of workers in high-wage nonroutine occupation is empty. This corresponds to a state where routine technology is too low. Obviously, the case $a_1 > \frac{w_r}{w_n} a_2$ never exists under imperfect substitution of tasks since when routine worker set is empty the demand for routine dramatically increases, which boosts the relative routine wage until routine set is nonempty. The condition in the main text assures that each occupation has positive employment of both skill types in equilibrium.

Figure 6: Worker-Occupation Assignment and Relative Taks Price



The figure shows on the vertical axis the potential worker wage relative to nonroutine task wage as a function market quality (θ) on the horizontal axis. Upper scripts 0 and 1 correspond to different relative task wage levels.

prefers low-wage nonroutine, between $\overline{\theta}_L$ and $\overline{\theta}_H$ she prefers routine, and above $\overline{\theta}_H$ she prefers high-wage nonroutine. Consequently, $\frac{\overline{\theta}_L}{h}$ and $\frac{\overline{\theta}_H}{h}$ are the cut-off values for the high-skill worker.

A simple consumption side closes the model. The final output is consumed by the built-in representative household whose income is composed of wage income of all workers. The household expenditure simply equals total wage income.

While the model is based on a static setting, different time periods can be characterized by the monotonically changing state of relative task technologies. The following proposition summarizes the impact of routinization in the model described above.

Proposition: *Suppose that $\epsilon < 0$, and routinization is defined by higher relative technology growth in routine tasks, i.e., $\frac{A_r}{A_n}$ is increasing. Then routinization leads to (i) polarization of employment when occupations are ranked by wages and skill-biased occupation growth when ranked by skill shares; (ii) a*

U-shaped trajectory of low-wage worker share in nonroutine employment.

The formal proof is provided in the Appendix section A.3. The result of the proposition on polarization comes from the same mechanism of the structural change models with uneven technology growth (e.g., Ngai and Pissarides, 2007; Goos et al., 2014). Higher relative technology growth of routine tasks increase the efficiency in those tasks, which leads to higher demand for nonroutine tasks since two task types are poor substitutes. The relative wage of nonroutine tasks increases, which leads to worker flows into the tails of wage distribution. This is shown as a clockwise rotation of the relative routine wage schedule relative in Figure 6. The cut-off for low-wage (high-wage) workers increases (decreases), leaving less workers in the routine occupation.

Key in the skill-biased occupation growth result is the skill-intensity ranking. The higher skill ranking of high-wage jobs is straightforward since the cut-off for high-skill worker ($\frac{\overline{\theta}_H}{h}$) is always smaller than the low-skilled cut-off ($\overline{\theta}_H$). Consequently, the skill intensity in high-wage occupations is always greater than others. The skill intensity comparison between routine and low-wage depends on the distribution. In the uniform case they always have the same skill ranking, which is a good approximation of the data.[21] Allowing skill heterogeneity in all occupations leads to the reconciliation of the occupation growth trends observed in the US economy.

The second interesting result of the model is that relative employment share of high-wage to low-wage nonroutine occupations is U-shaped. In the earlier phases of routinization the employment reallocation out of routine jobs relatively favors high-wage occupations, whereas later the lower-wage nonroutine job growth takes the lead. This prediction of the changing time pattern of polarization is consistent with the decadal changes in growth patterns and could explain why polarization evolves since the early 2000s in a way to imply the reversal of the demand for cognitive tasks that is documented by Beaudry et al. (2016).

[21]See Figure A.1. Generalizing this result for distribution with non-linear CDF requires departing from identical distributions for skill types. For instance, when quality follows exponential distribution the scale parameter for variance should be higher in high-skill distribution.

The non-linear dynamics of lower tail's share in the second part of proposition is the result of the non-linearity of wage schedules in nonroutine tasks. In order to have an intuition for this result first consider the primitive state of technology when the relative nonroutine technology is small. In particular, in a state where $a_2 \frac{w_r}{w_n} > a_3$ the set of high-wage nonroutine workers is empty while there is positive levels of employment in low-wage jobs. As routine-biased technology advances there comes a point where the high-quality cut-off is below unity and the ratio of low-wage to high-wage workers in nonroutine employment sharply diminishes from infinity. On the other hand, as both high- and low-wage employment accumulates, the share of low-wage starts increasing again because of the smaller slope of the low-wage efficiency schedule. Consider the extreme case in which the low-wage slope is zero and high-wage is infinity, where routinization does not induce any change in high-wage cut-off, while the impact on low-quality cut-off is maximal.

A final remark illustrates how the framework is also linked to the canonical SBTC model. The exogenous relative skill supply k, and relative efficiency of high-skill h is fixed in this analysis. However, both the relative supply and demand for skill has been on the rise (Katz and Murphy, 1992; Acemoglu and Autor, 2012). These trends clearly do not affect the model's result on skill-biased occupation growth and polarization result, as well as the U-shaped course of low-wage occupation's share in nonroutine employment within each skill type. However, it may alter the latter result in the aggregate employment particularly if both skill supply and demand grow excessively. Appendix Figure A.7 demonstrates a quantitative example using estimates of relative skill demand and supply from the Census extracts, which compares the predictions of the model in each decade with the actual low-wage shares. The model does a good job in capturing the U-shape of the aggregate low-wage share in total nonroutine employment even in this simple form.

6 Concluding Remarks

In this research I document skill-biased occupation growth as a robust and continuous fact of the US labor market. The long run pattern for the dynamics of employment and wages across occupations depends crucially on the metric used to measure skill. Polarization is an outcome only when skill is proxied by occupational wages. Other and more direct metric for skills, namely share of college workers and college graduates, mean years of education, cognitive ability, skill requirement, and training, are more consistent with monotonic growth pattern. The implication of these findings is that the skill-based interpretation of polarization should be approached with caution. The evidence calls for a multi-faceted approach regarding tasks and skills in the assessment inequality trends.

I argue that the reconciliation can be achieved through adopting a more data-consistent approach to skills within the existing conceptual models of technological change. The models of routinization starting with Autor et al. (2003) proved the importance of differentiating tasks from skills, which are inherently the same in the canonical SBTC model. However, a common theme in both the standard SBTC and routinization frameworks is the one-to-one mapping of skills to tasks either absolutely or conditional on the technology. I suggest that an extended version of the routine-biased technical change model that unconditionally allows for skill heterogeneities within occupations is capable of explaining different shades of occupational growth trends.

Overall, my findings encourage future research towards the development of a more sophisticated understanding of the relevant skills and wage determination at the low-wage jobs in an environment where the evolution of the employment structure continues to be skill-biased throughout the labor market.

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APPENDIX OF SKILL-BIASED OCCUPATION GROWTH

A.1 Data Appendix

A.1.1 Census and ACS

The Census data cover 1980, 1990, 2000 Census 5% extracts, 2005 and 2010 surveys of ACS.[22] The sample includes workers of age 16-64, employed workers excluding armed forces and self-employed who reported positive wage income. Employment of an occupation is total annual hours worked computed as usual weekly hours times weeks worked variables. Labor supply weights are calculated as annual hours times population weights. Wage income is subject to top-code treatment such that top-coded observations are multiplied by 1.5. Real wages are computed in terms of 2010 dollars and the adjustment is done by PCE index. Real hourly wages are computed as real annual wage income divided by annual hours. For each sample year I assign real hourly wages smaller than the first percentile of wage distribution equal to the first percentile's real hourly wage.

A.1.2 Task Variables Used in Table 3

I use the relevant aspects of the three-task view (abstract, routine, manual) computed from DOT in a similar way by Autor and Dorn (2013). From the occupational network (O*NET) database published by the US Department of Labor I obtain three additional task complexity variables as proxies for working conditions.[23] One indicates how demanding a job is in terms of working time with a structural job characteristics measure

[22] Census/ACS data are obtained from the IPUMS database (Ruggles et al., 2017).

[23] According to ILO, "... working conditions cover a broad range of topics and issues, from working time (hours of work, rest periods, and work schedules) to remuneration, as well as the physical conditions and mental demands that exist in the workplace" (URL: http://www.ilo.org/global/topics/working-conditions, Access date: 20.03.2018).

of "the typical length of workweek". The other provides a proxy for mental demands of the job by the work activity variable "analyzing data or information". Last one is a combined measure of hazardous conditions of the job computed as an average of several related physical work conditions variables.[24] I merge the SOC 2010 codes provided by O*NET to the dataset using 2010 ACS's reported SOC codes and 2010 labor supply weights.

A.2 Occupational Classification

A.2.1 Sensitivity of Long-Run Monotonicity to Occupational Classification

All the analysis in the paper is performed using the occupational classification of Dorn (2009). In addition, there are two more occupation categories provided by IPUMS Census that are comparable across Census waves, namely *occ1950* and *occ1990*.[25] These two classifications are inclusive of all the existing occupations but are not balanced in the sense that some occupations in later years do not exist. David Dorn's classification, *occ1990dd*, is an improved version of Meyer and Osborne (2005)'s modification on 1990 Census 3-digit occupation codes (*occ1990*) and provides a balanced set of occupations. Nevertheless, it involves merging of more detailed Census occupation codes and this has the potential of affecting the results. Therefore in order to enable comparison, in this subsection I present the graphical analysis regarding different occupation codes suggested by Census.

Figure A.3 shows long run smoothed employment share and log real wage changes by skill percentiles of college share of employment in 1980 calculated according to different occupation classifications. Under all classifications I confirm the key long-run observation of monotonic occupation employment and wage growth by skill intensity.

[24] Following variables are included in the hazard measure: "Deal With Physically Aggressive People", "Deal With Unpleasant or Angry People", "Exposed to Contaminants", "Exposed to Disease or Infections", "Exposed to Hazardous Conditions", "Exposed to Hazardous Equipment", "Exposed to High Places", "Exposed to Minor Burns, Cuts, Bites, or Stings", "Exposed to Radiation", "Exposed to Whole Body Vibration", "Extremely Bright or Inadequate Lighting", "Very Hot or Cold Temperatures".

[25] See Meyer and Osborne (2005) for a related working paper that provides a comparison of two classifications in depth.

A.2.2 Occupational Employment Growth in the 1990s

Although the main indicator for job polarization in the literature is occupational employment changes by occupations' wage percentiles, there are two influential papers Autor et al. (2006, 2008) that report non-monotonic employment changes along occupational mean education, particularly between 1990 and 2000. Since these findings seem to contrast with my observation on monotonic demand growth along the skill distribution, it is important to explore the source of difference between this paper and others. Therefore I provide a discussion on results of earlier papers here. I approach to untangle the set of puzzling results by directly using data released in David Autor's web page regarding Autor et al. (2008).

The main practical difference between my paper and the two papers documenting polarization along education percentiles is the occupational classification. Autor et al. (2008) use *occ1990* while this paper employs *occ1990dd*. As discussed in the preceding section the two coding schemes lead to similar observations of employment changes in the long-run, but this might not be the case in smaller frames of time. In order to be certain that occupation coding preference is the true source of divergence, next I report the results of the following data exercise. Autor et al. (2008) provide their dataset including both *occ1990* and original Census codes *occ* in 1980, 1990, and 2000. Merging these *occ* codes to *occ1990dd* from the crosswalk provided by David Dorn, I redo the analysis in Autor et al. (2008) on the basis of *occ1990dd* instead of *occ1990*.

Figure A.4 shows the smoothed employment share changes according to two different occupation codes. The upper panel replicates Autor et al. (2006) and Autor et al. (2008) and shows smoothed 1980-1990 and 1990-2000 changes by mean years of education percentiles where occupations are in *occ1990* codes. The lower panel shows the same with *occ1990dd* codes. The comparison between two suggests that the particular trend in occupational employment growth during 1990s depends on occupation definitions.

Considering that *occ1990dd* is an improved version of *occ1990*, and that in the long-run two codes lead to similar patterns of employment demand changes as I show in Figure A.3, the striking contrast may seem puzzling. For this reason, I compare two coding schemes based on their stability of occupation coverage in Autor et al. (2008)'s data. *occ1990dd* have 330 number of occupations with non-zero employment share in 1980, 1990, and 2000. There is little change in terms of representation of occupations. On the contrary *occ1990* reports 381 occupations in 1980, 380 in 1990 while there is only 336 in 2000. The difference between 1980 and 2000 coverage corresponds to around 3 percent of 1980 employment. The instability of *occ1990* might lead to inconsistency in terms of comparison of employment between 1980 and 2000 since each percentile is assumed to contain 1 percent of employment. Therefore percentiles formed according to employment shares can be misleading when using *occ1990*.

Finally, I check whether *occ1990* based figures imply polarization when a simpler method is used. Instead of forming percentiles of employment using employment shares I directly generate percentile rank of occupations by education. Also, since employment shares suffer from occupational inconsistency under *occ1990*, I directly use occupational employment growth. Figure A.5 shows smoothed 1990-2000 log change of employment sorted by education percentiles in 1980. In order to see how my own sample compares with theirs I do the exercise both with Autor et al. (2008) data and with the one used in this paper. Although *occ1990* codes do not indicate a sharp monotonic rise in 1990s when sorted by mean years of education, the resulting pattern surely does not imply polarization. The observation is also confirmed by the smoothed line from the data of this paper using *occ1990* and the same method, which suggests that differences between the observations of Autor et al. (2006, 2008) and mine do not stem from sample or methodological differences.

In summary, the previous literature's direct evidence on employment polarization by education is not robust to the occupation codes used. Particularly, from 1990 to 2000 the coverage of *occ1990* significantly shrinks which makes smoothed graphs based on employment percentiles much less comparable between the periods. Hence *occ1990dd* used in later studies of labor market polarization (e.g., Autor and Dorn, 2013) provides a more reliable comparison which supports the monotonic employment growth by skill shares that is observed in this paper during each decade after 1980.

A.3 Theory Appendix

A.3.1 Proof of Propositon

At the cut-off quality, the following condition holds for the worker who is indifferent between high-wage non-routine and routine task:

$$a_3\overline{\theta}_H - c_3 = \frac{w_r}{w_n} a_2 \overline{\theta}_H \tag{A.1}$$

Similarly, the indifference condition between low-wage non-routine and routine is given by:

$$a_1\overline{\theta}_L + c_1 = \frac{w_r}{w_n} a_2 \overline{\theta}_L \tag{A.2}$$

Combining equations (A.1) and (A.2), the two cut-offs are related as in the following:

$$a_3 - \frac{c_3}{\overline{\theta}_H} = a_1 + \frac{c_1}{\overline{\theta}_L}, \tag{A.3}$$

which simply suggests that the two cut-offs can only change in the opposite direction.

First order conditions imply the following relationship between efficiency wages and effective supply:

$$\left(\frac{A_n}{A_r}\right)^{\epsilon} \frac{w_r}{w_n} = \left(\frac{\overline{\theta}_H{}^2 - \overline{\theta}_L{}^2 + k\left(\left(\frac{\overline{\theta}_H}{h}\right)^2 - \left(\frac{\overline{\theta}_L}{h}\right)^2\right)}{1 + \overline{\theta}_L{}^2 - \overline{\theta}_H{}^2 + k\left(1 + \left(\frac{\overline{\theta}_L}{h}\right)^2 - \left(\frac{\overline{\theta}_H}{h}\right)^2\right)} \right)^{\epsilon-1}, \tag{A.4}$$

Since $\epsilon < 0$, the first term with relative technology on the LHS in equation (A.4) is increasing in routinization. Suppose that $\overline{\theta}_L$ decreases. Then from equation (A.3) $\overline{\theta}_H$ should increase and this is only possible if $\frac{w_r}{w_n}$ rises. Then the RHS of equation (A.4) decreases, which would contradict the increasing

LHS. Therefore the cut-offs move in a way to decrease the set of routine workers, the relative efficiency wage of routine-workers, and the effective relative supply of routine task. Polarization result immediately follows because routine worker wages lie in between both types of non-routine worker wages.

The high- and low-skill employment in high-wage nonroutine task are $k\left(1-F_S\left(\frac{\overline{\theta}_H}{h}\right)\right)$, and $\left(1-F_U\left(\overline{\theta}_H\right)\right)$, respectively. Consequently, the skill share is always highest in high-wage occupations. Under uniform distribution, high- to low-skill employment ratio is $\frac{k}{h}$ in both routine and low-wage nonroutine occupations. Therefore, when occupations are ranked by skill intensity, the lowest rank is shared by these two group of workers. Consequently, routinization always leads to skill-biased occupation growth. This concludes the first part of the proof.

Next, I study the comparative statics of low-wage to high-wage non-routine employment with respect to technological change. Using equation (A.3) the fraction can be expressed by $\overline{\theta}_L$:

$$\frac{\text{low-wage employment}}{\text{high-wage employment}}=\left(\frac{1+k}{\left(1+\frac{k}{h}\right)\overline{\theta}_L}-\frac{c_3}{\overline{\theta}_L\left(a_3-a_1\right)-c_1}\right)^{-1}, \tag{A.5}$$

which is minimized at $\overline{\theta}_L=\frac{c_1}{(a_3-a_1)}\left(\frac{c_3(a_3-a_1)\left(1+\frac{k}{h}\right)}{1+k}\right)^{-\frac{1}{2}}$ over the domain of possible lower quality cut-off, i.e., $\frac{c_1}{a_3-a_1-c_3}<\overline{\theta}_L<\frac{c_1+c_3}{a_3-a_1}$. Inspecting the first derivative of equation (A.5) reveals that the share is decreasing before the critical point and increasing at higher values. This completes the second part of proof.

■

Table A.1: Employment Share Change and Skills

(Dependent Variable: Change in Occupational Employment Share, 1980-2010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage	-8.26	0.09						
	(2.86)	(0.28)						
Wage Squared	1.58							
	(0.55)							
College Share			0.13	0.90				
			(1.40)	(0.20)				
College Share Squared			0.78					
			(1.39)					
Years of Sch.					-0.16	0.12		
					(0.50)	(0.03)		
Years of Sch. Squared					0.01			
					(0.02)			
AFQT							-0.31	0.13
							(0.34)	(0.04)
AFQT Squared							0.04	
							(0.03)	
Constant	10.48	-0.45	-0.44	-0.57	0.13	-1.69	0.20	-0.84
	(3.69)	(0.79)	(0.23)	(0.15)	(3.29)	(0.41)	(0.81)	(0.24)
R^2	0.06	0.00	0.12	0.12	0.10	0.10	0.08	0.06

	(9)	(10)	(11)	(12)	(13)	(14)
GED	-0.59	0.21				
	(0.67)	(0.07)				
GED Squared	0.10					
	(0.08)					
Training (DOT)			-0.01	0.06		
			(0.13)	(0.04)		
Training (DOT) Squared			0.01			
			(0.02)			
Training (O*NET)					0.19	0.10
					(0.10)	(0.03)
Training (O*NET) Squared					-0.01	
					(0.01)	
Constant	0.47	-0.98	-0.29	-0.35	-0.51	-0.42
	(1.22)	(0.26)	(0.16)	(0.14)	(0.18)	(0.14)
R^2	0.08	0.06	0.03	0.02	0.08	0.07

Numbered columns shows the coefficients estimated by OLS from the regression of 1980-2010 occupational employment share changes on the corresponding skill measure shown in the rows. Wages, years of schooling and college share are computed from 1980 Census. See data section in the main text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses.

Table A.2: Wage Growth and Skills

(Dependent Variable: Change in Mean Log Real Wage, 1980-2010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage	-1.48	0.08						
	(0.55)	(0.05)						
Wage Squared	0.30							
	(0.11)							
College Share			0.97	0.38				
			(0.18)	(0.06)				
College Share Squared			-0.60					
			(0.21)					
Years of Sch.					0.26	0.05		
					(0.10)	(0.01)		
Years of Sch. Squared					-0.01			
					(0.01)			
AFQT							0.08	0.08
							(0.05)	(0.01)
AFQT Squared							-0.01	
							(0.01)	
Constant	1.98	-0.07	-0.09	0.01	-1.84	-0.49	-0.23	-0.22
	(0.69)	(0.13)	(0.03)	(0.02)	(0.65)	(0.11)	(0.12)	(0.04)
R^2	0.07	0.02	0.45	0.39	0.39	0.35	0.42	0.32

	(9)	(10)	(11)	(12)	(13)	(14)
GED	0.07	0.12				
	(0.11)	(0.02)				
GED Squared	0.01					
	(0.02)					
Training (DOT)			0.03	0.03		
			(0.03)	(0.01)		
Training (DOT) Squared			-0.01			
			(0.01)			
Training (O*NET)					0.11	0.05
					(0.02)	(0.01)
Training (O*NET) Squared					-0.01	
					(0.01)	
Constant	-0.18	-0.27	0.08	0.08	-0.01	0.06
	(0.20)	(0.06)	(0.04)	(0.02)	(0.02)	(0.02)
R^2	0.35	0.35	0.15	0.15	0.40	0.34

Numbered columns show the coefficients estimated by OLS from the regression of 1980-2010 occupational mean log real wage changes on the corresponding skill measure shown in the rows. Wages, years of schooling and college share are computed from 1980 Census. See data section in the main text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses.

Figure A.1: Smoothed Occupational Education Intensity by Wage Structure

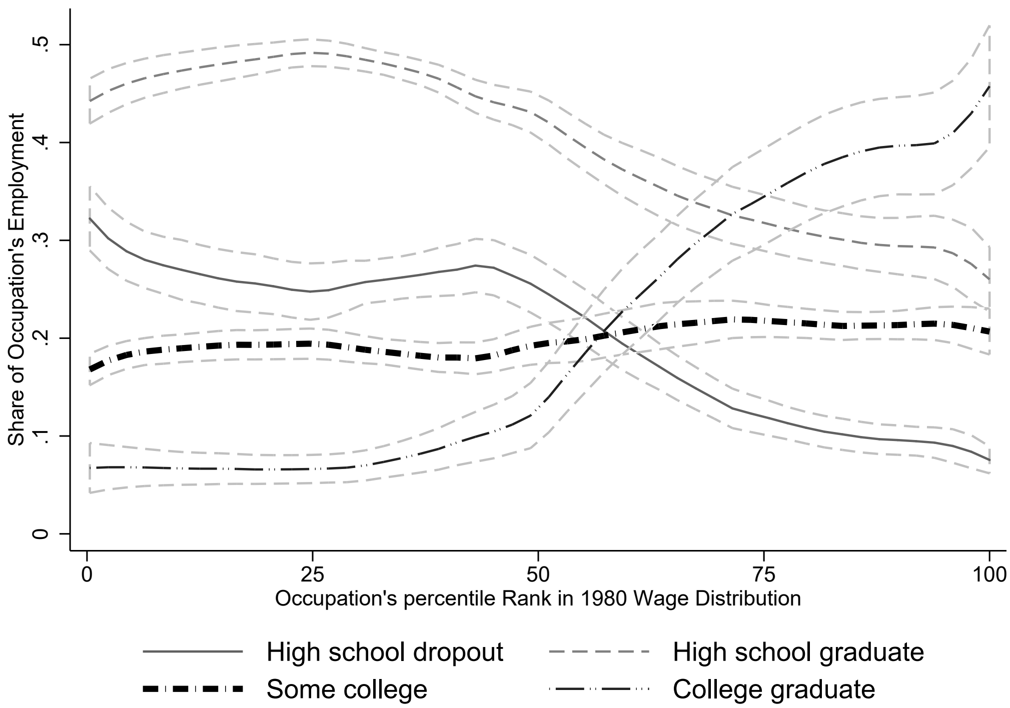
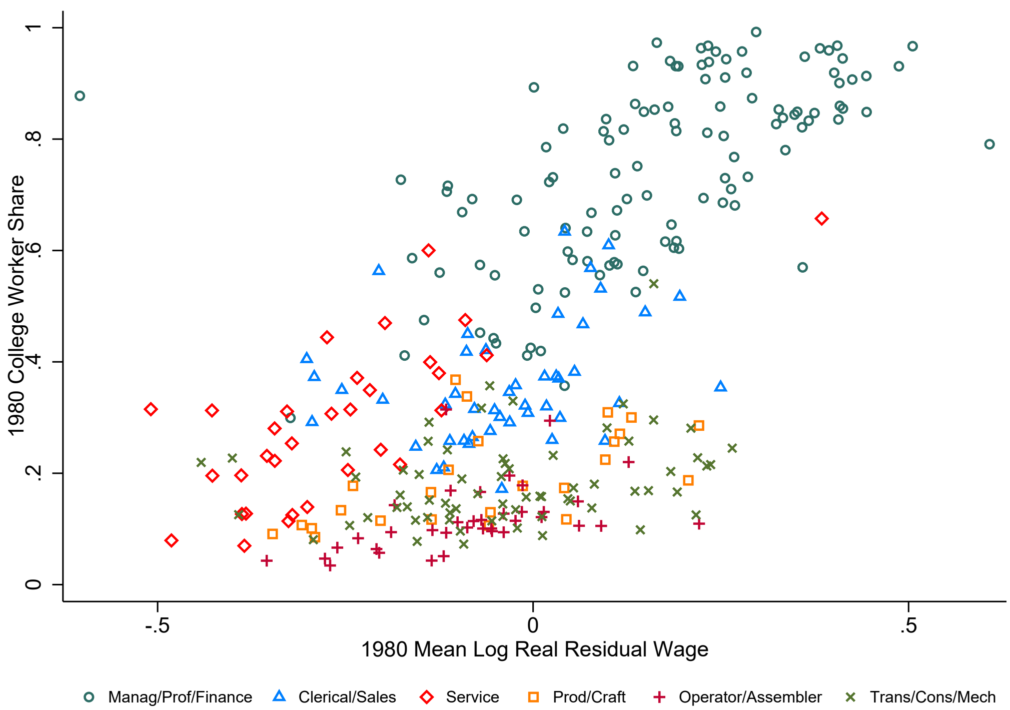


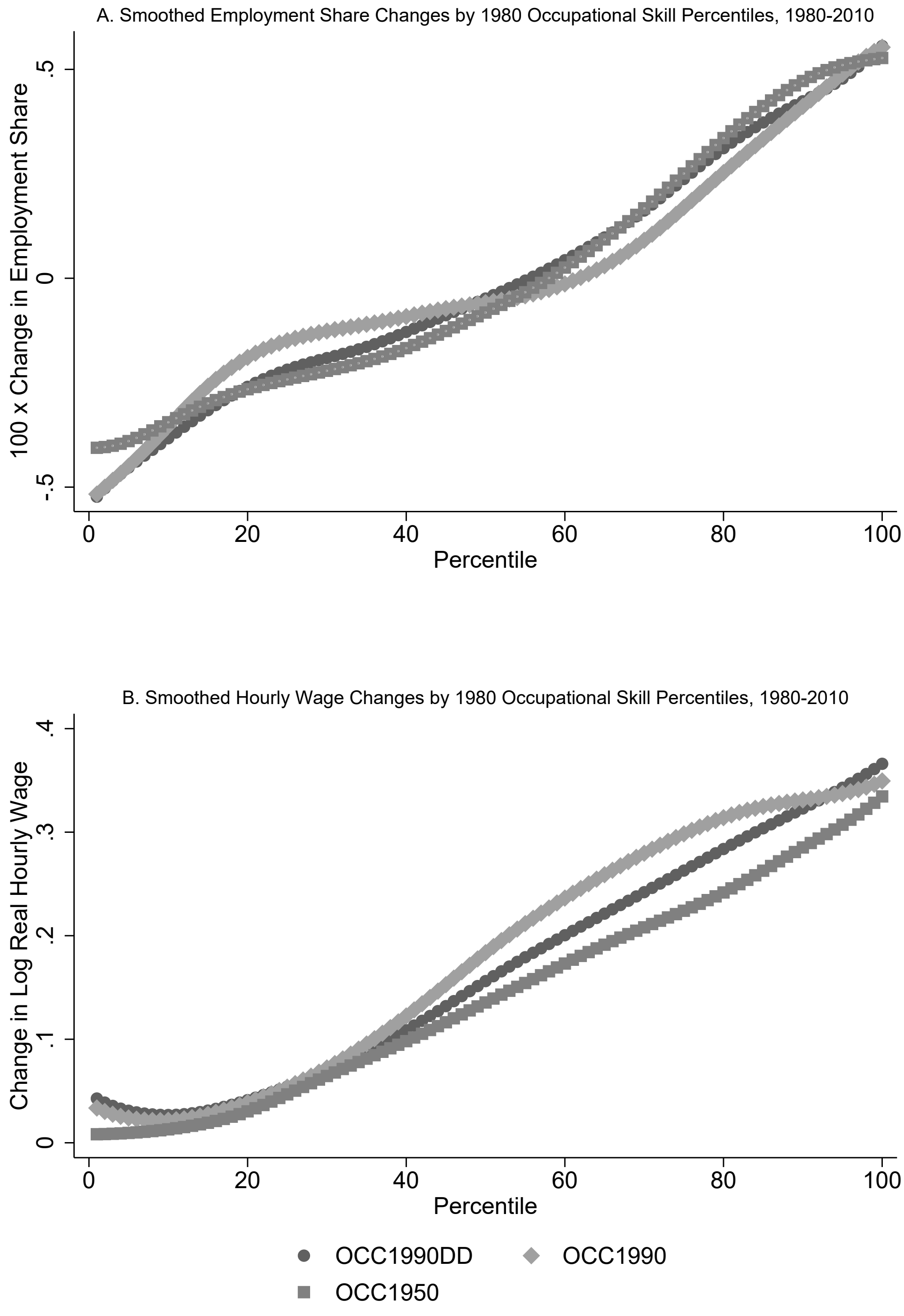
Figure shows smoothed shares of each skill group in occupations' employment in 1980 by the 1980 occupational mean wage percentile rank. Smoothing is based on 323 consistent occupation codes following Dorn (2009)'s classification and performed by local polynomials of degree 0 with bandwidth of 10 and weighted by 1980 occupational employment shares. Employment shares and mean wages are calculated using labor supply weights in 1980 Census, that is Census weight times total annual hours worked for each individual. Smoothed points may not sum up to one since smoothing is done separately for each skill-group.

Figure A.2: Occupational Skill Intensity and Residual Wages



Residual wages are obtained from regressing 1980 Census individual log hourly real wages on years of schooling, a quartic of age, dummies of gender, race and metro status. Labor supply weighs are used in all calculations.

Figure A.3: Monotonic Occupation Growth and Occupation Classification



The figure shows smoothed 1980-2010 changes in occupational employment shares and real log wages of occupations ranked by 1980 share of college workers in occupations' employment according to different occupation codes. See text for details on occupation codes. For all other details see Figure 2 notes.

Figure A.4: Smoothed Changes in Employment Share by Skill Percentile and Occupation Codes

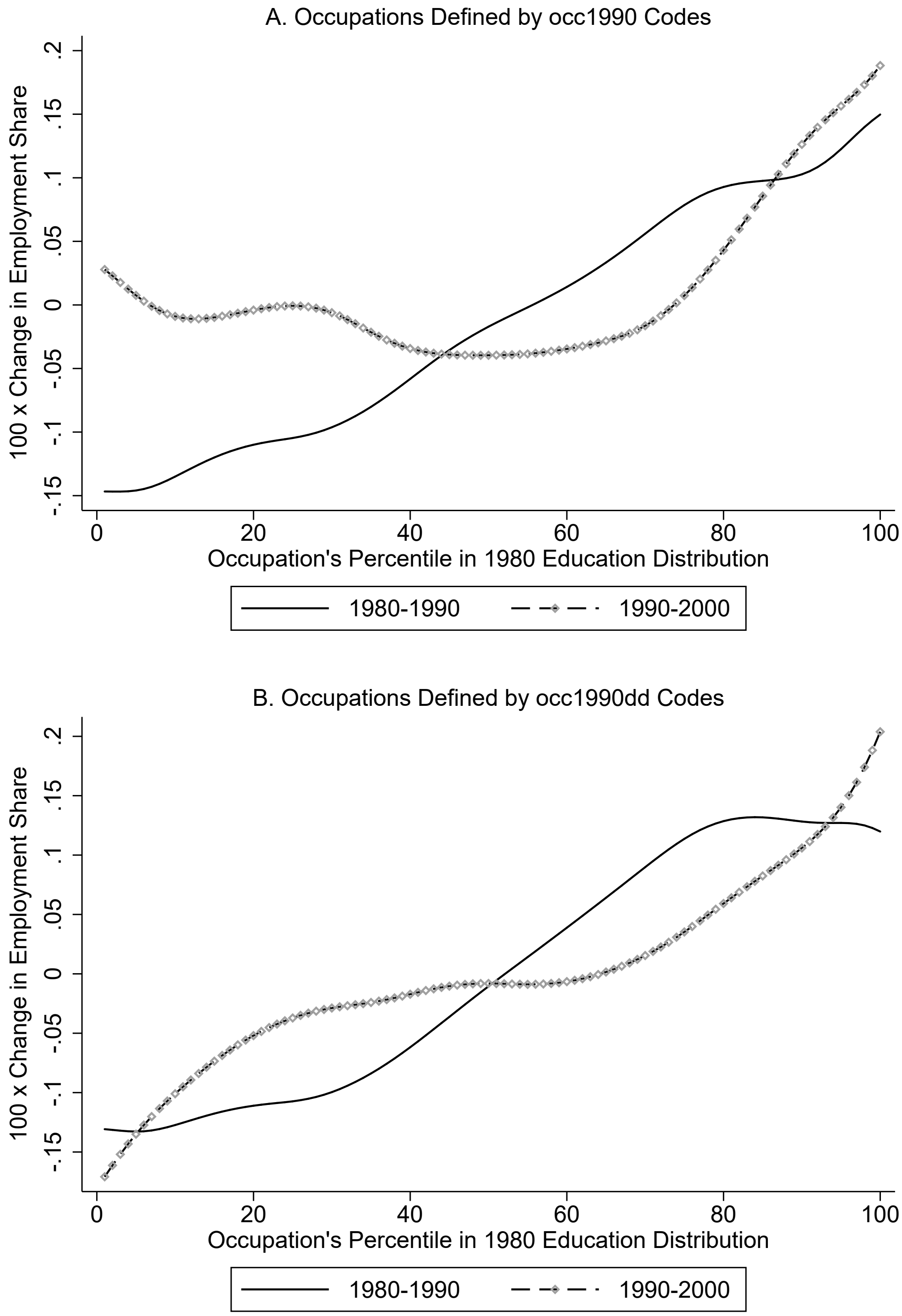


Figure shows smoothed 1980-1990, and 1990-2000 employment share changes in occupational employment percentiles using the two occupation code system. Percentiles are ordered by occupational mean years of education in 1980. The data and smoothing procedure follows Autor et al. (2008). *occ1990dd* occupation codes are merged to the original data by a crosswalk from Autor and Dorn (2013).

Figure A.5: Smoothed Occupational Employment Growth of *occ1990* Occupations

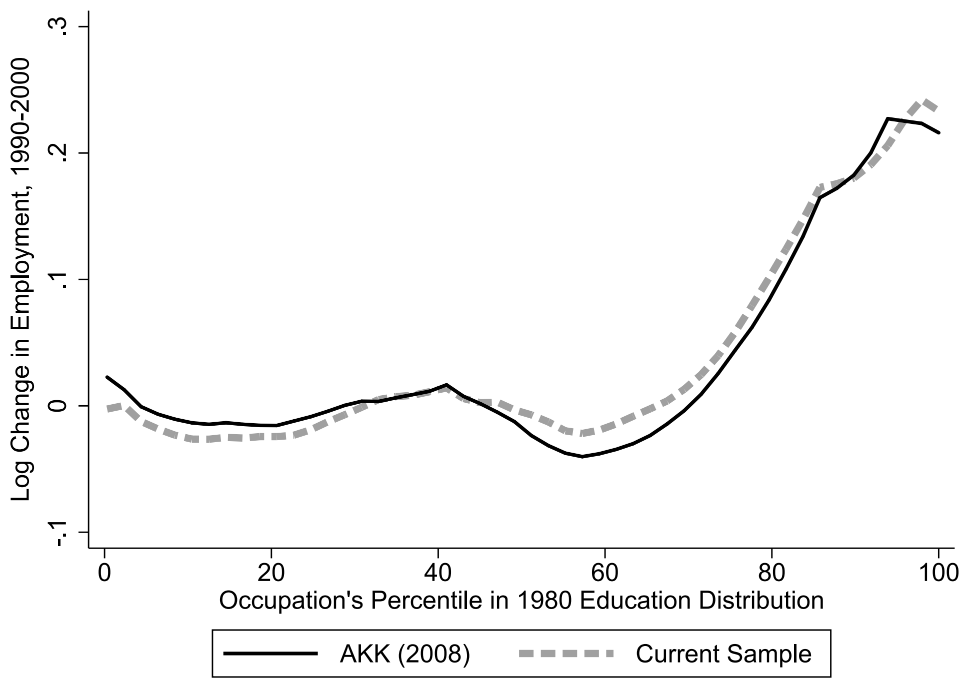
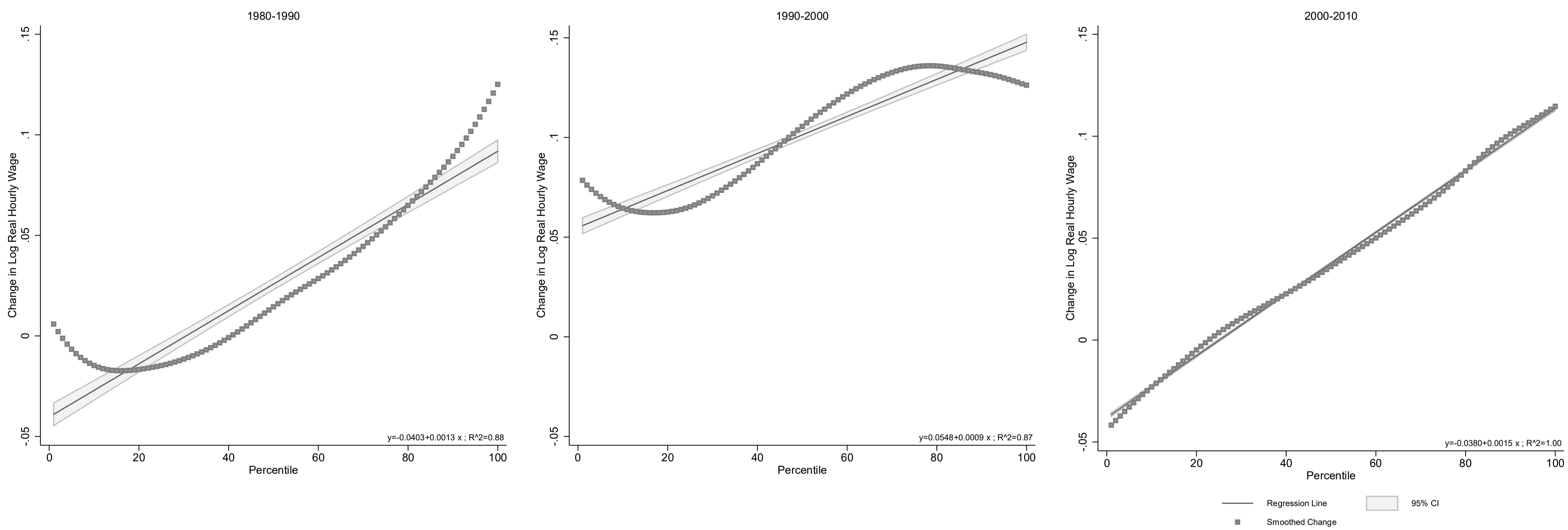


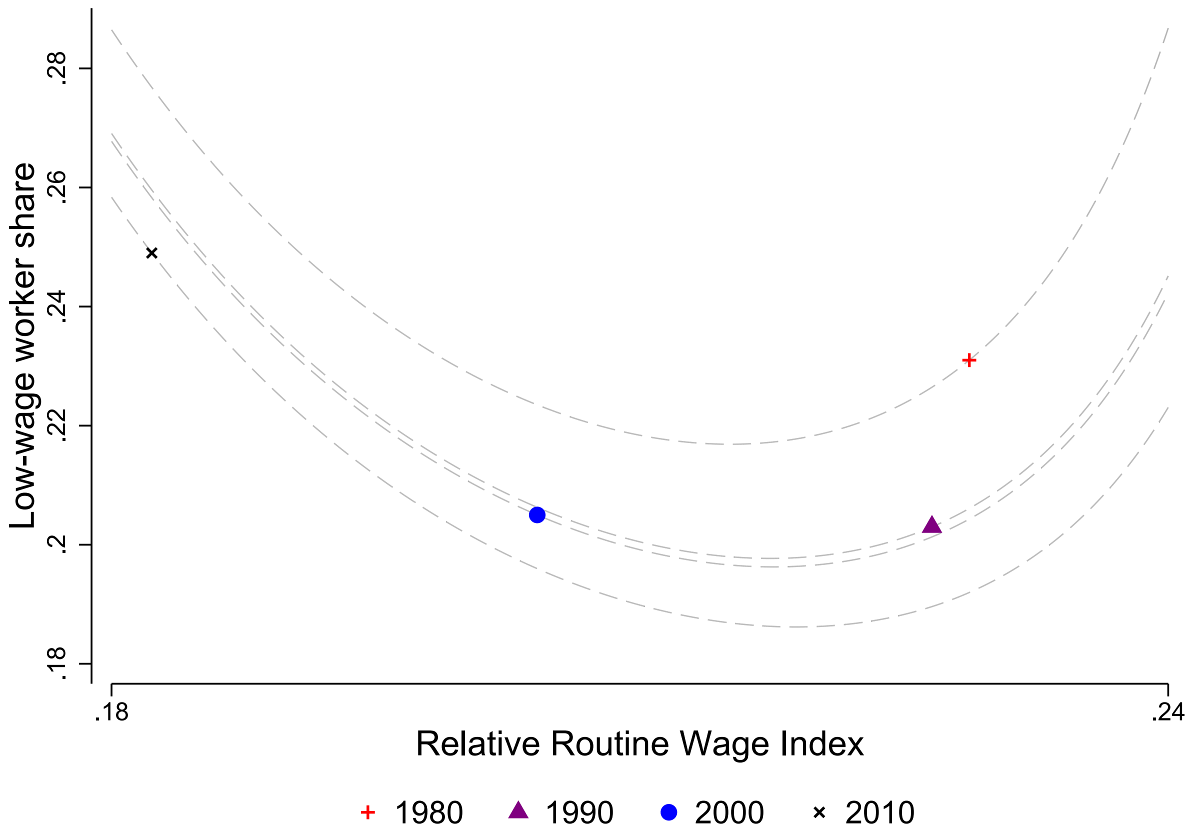
Figure shows smoothed 1990-2000 employment growth by occupational employment percentile ranks using *occ1990* codes. Percentile ranks are based on occupational mean years of education in 1980. The smoothing is done by local polynomial smoothing with bandwidth 10 and weighted by 1980 employment. AKK(2008) indicates that the data used is Autor et al. (2008). Current sample indicates the data used in this paper.

Figure A.6: Decadal Trends in Real Wage Growth



Notes: The figure shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in log real hourly wages of occupational employment percentiles ranked by 1980 share of college workers in occupations' employment. Square points represent the smoothed points. The solid line represents the linear fit of smoothed points with 95 percent confidence interval indicated as shaded areas. The equation shows the OLS coefficients and R^2 from the regression of smoothed points on skill percentiles.

Figure A.7: Model's Prediction on the Low-Wage Worker Share in Nonroutine Employment, 1980-2010



The figure illustrates a numerical exercise on the low-wage worker share in total nonroutine employment. Each dashed curve shows the relationship between relative nonroutine wage index and share of low-wage worker in total nonroutine employment under different values of k and h. Points indicated by markers of different shapes show the actual low-wage workers share at each decade from 1980 to 2010. The model parameters are set to $a_1 = 0.14$, $a_3 = 0.3$, $c_1 = 0.01$, $c_3 = 0.005$. k for each decade is calculated as the total hours of college workers divided by the total hours of noncollege workers from Census. h in each decade is the exponential of college worker dummy's coefficient from the regression of log hourly wages with additional regressors of gender, race, and three occupation dummies, and a quartic of potential experience in each year. Relative nonroutine wage index is defined by $a_2 \frac{w_r}{w_n}$. Definitions of low-wage nonroutine, routine, and high-wage nonroutine occupations are adopted from Autor and Dorn (2013). The implied relative wage index solved for the actual low-wage employment share in nonroutine employment, relative college worker supply and college premium is consistent with the decline of relative routine wages.

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