# SKILL-BIASED OCCUPATION GROWTH*

ORHUN SEVINC

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*This paper documents that employment and wage growth of occupations increase monotonically with measures of skill intensity since 1980 in the US. Skill-biased occupation growth is not driven by a specific time period, gender, age group, or occupation classification. The simultaneous occurrence of skill-biased occupation growth and polarization along wages is a result of the weak connection between wage and skill structure among the low-wage jobs. Trends in occupational change can be reconciled in an extension of the canonical skill-biased technical change model which incorporates skill type heterogeneity within occupations and occupation-specific disutility from work. Estimation of the model's college premium equation suggests a stable long-run growth for the relative skill demand.*

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## I. 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, Katz and Kearney, 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

[1]Polarization of employment is documented both in the US (Autor, Katz and Kearney, 2006, 2008; Autor and Dorn, 2013), the UK (Goos and Manning, 2007), and many other advanced economies (Goos, Manning and Salomons, 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.

tasks.[3]

A set of facts motivate the study of the implications of occupational skill heterogeneity. The first is the remarkable variation in skill intensity within occupations. Figure I plots the share of workers above high school education against mean log 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 1980. 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.[4]

Another implication of Figure I is that wages are not perfectly informative regarding the college share of occupations. Many so-called middle-skilled jobs contain less high-skill workers than the so-called low-skill service or clerical/sales occupations.[5] Figure II compares the wage percentile ranking on the horizontal axis with the difference between college share and wage ranking of occupations on

[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, Levy and Murnane, 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, Green and Sand (2016) who develop a model of two tasks which are jointly produced by high- and low-skill workers.

[4]Author's calculation using labor supply weights.

[5]The mismatch between occupational wages and education intensity is observed among all education groups as shown in Online Appendix Figure A.1. Online 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 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 decreasing 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.

The third fact is that polarization at the level of major occupation groups is common to both high- and low-skill workers. By each occupation group ordered by inital mean wages, the first two columns of Table I show the 1980-2010 change in the employment share (Panel A) and mean real wage growth (Panel B), separately for college and non-college workers. Some of the college workers not only choose to work in low-wage jobs in 1980, but more of them are reallocated into these jobs by 2010. It seems that the within-occupation skill heterogeneity is also important for the dynamics of occupation structure.

Lastly, growth patterns of occupations are not completely in contrast with their skill intensity. Last column of Table I reports the result of a simple exercise in which major occupations' employment share changes and wage growth from 1980 to 2010 are predicted by the initial skill intensity measured by college worker shares. Compared with the actual changes in the third column, although initial college share cannot perfectly predict the sizeable growth in service jobs or the stagnating wages of transportation, construction, mechanics, and mining occupations, it is able to deliver the non-monotonic employment and wage growth along occupational wages.

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 ability, and training measures. 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 decade after 1980, gender and age groups, and occupation classification. It is true that the US labor market has been polarizing, but it did not evolve into a market dominated by the most and the least skilled workers. Documenting the skill-biased occupation growth and establishing its robustness is the main contribution of this paper.

Next, I focus on the source of contrasting occupation growth patterns according to skills and wages by delving into the wage-skill disconnect at occupation level. Occupational wage is not a good predictor of education, cognitive ability, and training intensities for the lower half of the 1980 wage distribution. On the other hand, the bottom half of the wage distribution lines up remarkably well with working conditions reflecting mental demands, typical working hours, and exposure to hazardous conditions that exist in the workplace. The well-known trade-off between wages and the perceived difficulty of the job appears as a key in addressing differences in inequality trends.[6]

The empirical observations of the paper motivate a framework that extends the canonical SBTC model to occupations and assigns a key role to occupational skill heterogeneities. Occupations differ in the importance of high-skill worker in the performance of the job. For instance service occupations may welcome greater levels of high-skill chefs and nannies than construction jobs, but definitely not as much as surgeons. The economy-wide skill-biased technological change increases the demand for high-skill workers similar to the canonical SBTC model, and also affects the demand for occupations that utilize high-skill workers more intensively. Thus the interaction of skill-heterogeneity and SBTC act as an occupation-specific source of labor reallocation, which leads to skill-biased occupation growth when the substitutability of tasks across occupations is greater than substitutability across skill types within occupations. The model also produces non-monotonic occupation growth by wages if some of the least skill-intensive jobs impose greater levels of disutility from work.

There are other implications of the model supporting the usefulness of occupational skill heterogeneity in the evolution of inequalities. The most important is that extension of the canonical SBTC model to occupations seems to correct one of

[6]The idea that work and working conditions affect utility is old both in the economics (Smith, 1776) and psychology literature (Solomon, 1948). Among others, see Bryson and MacKerron (2017) on recent evidence on the negative impact of working on happiness; Kool et al. (2010) on the disutility provided by the mental effort; and Viscusi and Aldy (2003) for a review on the premium associated with the riskiness of the job. The economics literature widely uses models with leisure in the utility function which reflects the negative impact of working hours on utility.

the previously addressed shortcomings of the model (Acemoglu and Autor, 2012). Estimates from the canonical model's college wage premium equation suggest that the relative demand for college workers should have declined starting with the early 1990s, which has been found quite puzzling in the face of increasing use of computers in the workplace during the period (Goldin and Katz, 2008; Acemoglu and Autor, 2012). The analytical framework of this paper allows for a flexible way of estimating relative skill demand growth which does not require the time trend assumption. The college wage premium of the extended model estimates a stable growth rate of relative demand for high-skill worker since the 1960s.

This paper contributes to the task literature by offering a nuanced view regarding a well-known technological force and extending the list of the occupation-specific drivers of labor market inequalities.[7] The paper is also related to Beaudry, Green and Sand (2016) who also use an analytical framework that similarly allows for skill heterogeneity within occupations and assign a key role to high-skill workers in the occupation growth of low-wage jobs.[8] This paper mainly differs in its focus on occupation growth trends with respect to skill intensity rather than task-types and estimating a stable demand for skills for the last fifty years.[9]

[7]Among many others see Autor, Levy and Murnane (2003) on routine-biased technical change, Blinder (2009) on offshoring, Firpo, Fortin and Lemieux (2011) a unified analysis including deunionization.

[8]Beaudry, Green and Sand (2016) assume skill-based interpretation of polarization and consequently view the acceleration in the of lower tail employment after 2000 as the great reversal of skill demand. They also clarify in the paper that the reversal more specifically refers to cognitive tasks.

[9]Outside the task literature this paper is related to Cerina, Moro and Rendall (2017) who also argue that SBTC plays a key role in polarization through a multi-sector model with skill-, gender-, and sector-biased technical change.

## II. 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. In some parts of the empirical analyses, I also employ 6 major and 23 broader occupation groups constructed from the detailed occupations following Autor and Dorn (2013).

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.[10] I have two main skill variables generated from Census data, mean years of education and share of college workers.[11] 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

[10]Details on data cleaning and variable construction are provided in Online Appendix Section A.1.

[11]College worker is defined as having any level of college education.

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, Stixrud and Urzua, 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 US Department of Labor 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. I further use three additional variables from the database as proxies for working conditions.[12] One indicates how demanding a job is in terms of working time with a structural job characteristics measure 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.[13] I

[12] 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).

[13] 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

merge the SOC 2010 codes provided by O*NET to the dataset using 2010 ACS's reported SOC codes and 2010 labor supply weights.

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. In addition 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).

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".

## III. Occupational Skills and Trends in Occupation Growth

### III.A. 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 III 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. This is not completely surprising, but there are reasons for potential divergence. One reason could be that many workers with some college education but without a degree, which arguably does not add too much over a high-school degree compared to a college degree, are concentrated in some of the least paying jobs such as babysitters and waiters. Therefore college worker share could persistently rank this type of jobs towards the middle of distribution while college graduate share, similar to mean wages, might have suggested a lower place in the skill/quality hierarchy of occupations. Evidence in Figure III excludes such concerns.

Figure III leads to a puzzle when considering the consensus view on labor market polarization. From the perspective of SBTC, however, the interpretation could not be clearer. Just as the demand for high-skill workers, the relative demand for occupations that employ better skilled employees has increased over the last decades. However, it is too early to rule out the skill-based interpretation of polarization by looking at Figure III. Important questions are whether other measures of skills beyond college education are supporting the polarization observation, and whether the observed skill-biased occupation growth is driven by a certain decade, demographic group or treatment of occupations. In the remaining part of this section, I clarify the role of skills in the changing structure of occupational employment from several angles and shed light on the sources of the contrasting patterns.

### III.B. 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 III. 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 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 regressions 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. 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 $\Delta d_j$ 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 II 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.[14]

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 hum-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. Therefore I report in the forth rows

[14]Online 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.

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.[15] Last rows in both panels report the p-values associated with this test. The conclusion from Table II is that occupation growth over the long-run is significantly U-shaped only with wages.

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 measured by occupational wages. All other metric for skills, namely share of college workers, college graduates, mean years of education, ability, skill requirement, and training, are more consistent with monotonic pattern. The implication of these findings is that the skill-based interpretation of polarization should be approached with caution. In the following, I dig deeper to establish the robustness of this observation across time, gender and age groups, and then by occupational classification.

[15]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.

### III.C. Growth Patterns by Decade and Demographic Groups

*Occupation Growth in Each Decade*

SBTC hypothesis predicts a 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. Online Appendix Figure A.3 plots the tendency of employment share changes and real wage growth 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.[16]

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 from the figure. 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, Green and Sand (2016) who document a relative slow-down in the growth of highest-wage jobs. Maturity of organizational capital after 2000 followed by the

[16]Two related papers (Autor, Katz and Kearney, 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 Online 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.

expansion period in the previous decade is argued as the source of weaker growth in cognitive tasks. However, the persistence of monotonicity in job growth and the strong linear wage growth after 2000 in Online Appendix Figure A.3 suggest that the relatively lower demand for some of the high-wage cognitive jobs is not powerful enough to eliminate overall skill-biased occupation growth.

*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, Moro and Rendall, 2017). In order to see if the occupation growth with respect to skills differs by gender, Online Appendix Figure A.4 plots smoothed changes by college share of employment when the labor market is split by gender. The figure clearly indicates that the monotonic wage and employment changes take place within both gender groups.

The figure offers 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 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.

Figure A.4 therefore implies 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.[17] 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.[18]

*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 affected by the baby-boom cycle. Following the initial decline, the post-1980 period witnessed a sharp increase in the

[17] Among others see Blau and Kahn (2006) for the narrowing of the wage gap and its slow-down after 1980s and Goldin, Katz and Kuziemko (2006) for the disappearance of the gender college gap in the US.

[18] Goldin (2014) argues 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.

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.[19] 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 Online Appendix Figure A.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

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

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.[20]

Panel B presents the occupational wage growth by skills with respect to the three age groups. The result is 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 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.[21]

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

### III.D. Occupational Wage and Skill Structure

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 I provides an early insight: occupational wages in 1980 reflect skills well for the upper half of wage distribution,

[20] The exception is for occupations of highest skills. However, this is not predicted by the routine-biased technical change models, which hypothesize that workers in routine-intensive jobs are reallocated in the low-wage services occupations (e.g., Autor and Dorn, 2013).

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

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 present in Table III 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 A).[22] 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 $R^2$s 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.

Therefore in the determination of occupational wage structure, skill intensity does not appear to play the leading role particularly for the low-wage jobs, which clearly suggests that the rising demand in low-wage occupations does not imply a

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

trade-off between middle-skill and low-skill workers but something else.[23]

The literature on polarization often associates skill types with certain tasks. While majority of the models assume a hierarchy of skill types, task-specific skills that have different labor market price might also lead to the observed wage structure. Therefore as an alternative, I turn to the three-task view of routinization hypothesis (Autor, Katz and Kearney, 2006). According to the three-task view manual jobs have relatively lower productivity so that labor market return to working in those jobs is also low. On the other hand, abstract tasks involve a lot of complex thinking and interactions which are needed to solve the hardest problems and have the highest returns. Cognitive or non-cognitive routine tasks require precision which puts those jobs somewhere in between and dominate the middling jobs. Consequently, one expects to see the wage structure to associate negatively to manual task intensity and positively to routine task intensity for the lower half of the distribution. Furthermore, the upper half of the wage structure should be increasing in abstract intensity and decreasing in routine task intensity.

In Table IV the task characteristics are regressed on wage percentile ranking. First three columns show the association of three aspects of task complexity from Autor and Dorn (2013) with wages in the upper and lower half of occupational wage structure. Abstract task content and wages are positively related as expected but not

[23]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.

significantly for the low-wage jobs. Routine task intensity is positively related to wages for low wage jobs and inversely for high wage group as expected but lacks statistical significance. Contrary to the stylized view I do not find a declining wage structure with manual task intensity for the low-wage jobs. Despite its success in characterizing the task content of broader occupation groups (e.g., Acemoglu and Autor, 2011) the stylized three-task view seems incapable of capturing the 1980 wage structure at detailed occupation level.

Another task-based wage structure explanation 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 the last three columns of Table IV I use three task measures to quantify how demanding a job is. 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 mental 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 Section II. 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. All of the measures correlate well with wages for low wage group. For high-wage occupations wage structure is significantly associated with time and mental demand measures.[24]

While these simple conditional correlations do not aim to prove that wages are solely determined according to compensating differentials, the exercise is instructive in showing that the skill-based interpretation of polarization remains too naive in assuming lowest skills for occupations of lowest wages. An alternative explanation for interpreting the success of working conditions variables is that workers in low-wage occupations are overqualified and only get the returns from the required skills, whereas other jobs pay the marginal return from the actual skills. In this case the working conditions indicators could capture the task complexity differences across occupations and any premium on these tasks cannot be interpreted as evidence of compensating differentials. Under the alternative scenario the same worker who switches between two similar occupations is expected to get higher wages in the job with more demanding working conditions proportional to her ability level.

Using NLSY-1979 data on workers older than 22, I estimate the following equation to test the overqualification explanation.

[24]Online Appendix Table A.3 shows that individual wages are significantly and positively associated with all three measures in a micro log wage regression including controls for a quartic polynomial of age; dummies of educational attainment, gender, race, urban status; and a quadratic of routinization measure, and interactions for the first three set of variables. Furthermore, Online Appendix Figure A.6 shows that predicted wages by working condition variables do a good job in capturing polarization of both employment and wages.

$$\begin{aligned} \ln\left(\text{wage}_{ijt}\right) &= \gamma \text{WCI}_{ijt} + \gamma_1 \text{CS}_i \times \text{WCI}_{ijt} + \gamma_2 \text{SS}_i \times \text{WCI}_{ijt} \\ &\quad + \gamma_3 \text{CS}_i \times \text{SS}_i \times \text{WCI}_{ijt} + \beta X_{ijt} + \theta_i + \phi_t + u_{ijt}, \end{aligned} \tag{2}$$

where $wage_{ijt}$ is the hourly wage of worker $i$ at time $t$ in occupation $j$, $WCI_{ijt}$ is the working conditions index value of the occupation measured as the mean of the three working conditions variable discussed above, $CS_i$ is the worker's cognitive ability index, $SS_i$ is the worker's social skill index, $X_{ijt}$ is a vector of covariates including location variables, the interaction of age and years of education dummies, dummies for 23 broader occupations and 142 industries, $\theta_i$ is worker fixed-effect, and $\phi_t$ is the year fixed-effect. The working conditions index and skill variables are standardized to have zero mean and unitary standard deviation. The standard errors are clustered at the individual level.

The sample consists of individuals in the 1979 wave of NLSY between 1982 and 2000 who are older than 22. Using the data from Deming (2017) I merge the individual variables of NLSY with the task variables using a crosswalk between 1980 Census occupation codes and the *occ1990dd*. Cognitive skill measure is AFQT scores and social skill variable is the mean of self-reported sociability measures, high-school club and sports participation variables.[25]

[25] See Deming (2017) for the details of NLSY-1979 data and variables at the individual level.

Table V column (1), showing the estimation of equation 2 without the skill interaction terms, indicates that a worker who switches within the same broader occupation group and narrowly defined industry to a job that is one standard deviation higher in the working conditions index is paid 1.9 percent higher wages. Column (2) includes abstract, routine, and manual task intensities to address potential correlations with task complexity. Task complexity variables do not change the predictive power of the working conditions index. Column (2) also confirms the relatively poor performance of task complexity measures in explaining wage structure at detailed occupation level in Table IV. Column (3) estimates the baseline specification in equation (2). If overqualification explanation works then the interaction of individual skill measures and working conditions index should have positive and significant coefficients. Column (3) does not provide any significant evidence of higher returns to ability in more demanding jobs. The last column includes task complexity variables in the baseline specification, which does not change the results.

## IV. A Model of SBTC within Occupations

### IV.A. The Model

In this section I introduce an analytical framework that is consistent with the occupation growth trends, and the facts on the US wage and skill structure. The model is an extension of the canonical SBTC model of Katz and Murphy (1992).

The environment is essentially static and exogenous technical change is assumed. There are two types of worker skills which are imperfect substitutes and both contribute to the production of the task output of an occupation. The task production function at time $t$ for occupation $j$ is given by:

$$(3) \qquad T_{jt} = \left( (\beta_j)^{(1-\mu)} \left( A_{Ht} H_{jt} \right)^{\mu} + (1-\beta_j)^{(1-\mu)} \left( A_{Lt} L_{jt} \right)^{\mu} \right)^{\frac{1}{\mu}},$$

where $H_{jt}$ and $L_{jt}$ is the labor input by high-skill and low-skill workers respectively. There is no endogenous skill choice so total labor supplies $H_t$ and $L_t$ are exogenous in the model as in the canonical model of SBTC. The elasticity of substitution between skilled and unskilled workers that is constant across occupations is given by $\frac{1}{1-\mu}$, where $\mu < 1$. $A_{Ht}$ and $A_{Lt}$ represent skill-specific technologies which potentially grow in different and constant rates. In the SBTC literature, the bias of technology in favor of skills usually refers to the case when high-skill technology grows faster than technology of low-skill workers. Quantities of high- and low-skill labor is optimally chosen taking the price of task, $p_{jt}$, and wages for each input type, $w_{Hjt}$ and $w_{Ljt}$, as given.

$0 \leq \beta \leq 1$ measures occupation-specific relative importance of high-skill workers. The same task could be performed by both skill types though the skill intensities across occupations differ according to the importance of each skill type for the task output. For surgeons the weight of high-skilled worker in the production function can be assumed as maximum so only college workers can perform the job whereas for artists it can be lower, reflecting the fact that some of this activity could be performed by non-college workers. These weights can change but since skill structure is very stable in the long term, I assume them as fixed.[26]

Occupations' task output are combined in an aggregate production function to produce the final output which is then consumed. There is a final good sector where all task production is used as inputs as imperfect substitutes. The final good production function at time $t$ is the following:

$$Y_t = \left( \sum_{j}^{J} \gamma_j \left(T_{jt}\right)^{\rho} \right)^{\frac{1}{\rho}}, \tag{4}$$

where $Y_t$ is aggregate output, $T_{jt}$ is task output by occupation $j$ and total number of occupations is $J$. $\gamma_j > 0$ is the occupation-specific constant weight in production and $\rho < 1$. $\frac{1}{1-\rho}$ is the elasticity of substitution across occupations.[27] The output price is normalized to unity and firms take task prices as given. Firms in the final good sector choose inputs from occupations such that profits are maximized.

In sum, the production side of the model is simply an extension of the canoni-

[26]Online Appendix Figure A.7 compares the wage and skill structure in 1980 and 2010. Skill intensity is quite stable both in absolute terms and also when compared to the wage structure in 1980 and 2010.

[27]If one assumes a time varying version of $\gamma_j$ one can also study occupation-specific demand shifters with this model.

cal model to include occupations. The crucial distinctive feature of the model compared to the recent task-based SBTC models (e.g, Acemoglu and Autor, 2011; Autor and Dorn, 2013) is the joint presence of both skill types in the production of the same task output and the differences of high-skill weights across occupations. Therefore what characterizes occupational skills in this setting is the share or intensity of each skill type rather than the skill of a single type.

Wage inequality across occupations in the model is introduced through occupational variation of disutility from work (Rosen, 1986). This aims to account for the empirical observation in the previous section that the occupational wage structure only partially accords with the skill structure and strongly with task characteristics related to the disutility attached to the job.[28] I assume the simplest form of compensating differentials such that workers are homogeneous in preferences and skills, which can be relaxed to study a richer environment.[29]

In this model, workers experience a different level of satisfaction depending on the type of job they choose, in addition to the consumption provided through wage income. The consumer side is characterized by the following utility function for each worker with skill level $S$ working in occupation $j$:

[28] Another alternative to generate a wage structure that does not overlap with skill-intensity is to assume occupation-specific productivity distributions as in Roy-type models and orthogonality of direct skill measures to occupation-specific productivity.

[29] For instance, one can further assume that workers of each skill type are heterogeneous in terms of their sensitivity to disutility. Extensions with individual- and occupation-specific utiliy or ability shocks do not qualitatively affect the model's key result of SBTC as a driver of occupation growth.

(5) $$U_{Sjt} = \log(C_{Sjt}) - \log(d_j),$$

where $C_{Sjt}$ is consumption of final output by worker of skill $S = \{H, L\}$ who works in occupation $j$ at time $t$. $d_j$ is occupation-specific disutility of work. It is higher in jobs that are more demanding than others which reflects difficulty or risks associated with the task. The utility of worker of a given skill depends on the occupation decision.

Since the model is static there is no saving and the wage earned from working in occupation $j$ is fully consumed:

(6) $$C_{Sjt} = w_{Sjt},$$

where the wage $w_{Sjt}$ is the same for all workers of the same occupations and in the same skill group due to worker homogeneity.

Given task and skill prices, and exogenous levels of skill-specific technology, equilibrium in this economy consists of optimally choosen labor inputs of each skill type in each occupation that also satisfy the exogenous skill resource constraint; optimally determined task demand by final output firms; workers' optimal occupation decision taking into account the disutility from work; and households consuming all wage income such that total consumption equals total final output.[30]

### IV.B. Skill-Biased Occupation Growth

Reallocation of labor in the model depends on assumptions on the direction of the exogenous technical change. Skill-biased technical change, i.e., higher growth of economy-wide high-skill technology, combined with the model's key feature of occupational skill heterogeneity appear as a fundamental driver of the occupational reallocation of labor. The intuition is that substantial bias of demand growth towards high-skill workers also increases the demand for tasks that welcome high-skill workers relatively more. As a result, SBTC acts as an occupation-specific demand shifter in the economy. The following proposition summarizes the model's implications on occupation demand growth, which brings together the key empirical observations of this paper.

*Proposition 1:*

*Suppose that* $\frac{A_{Ht}}{A_{Lt}}$ *grows and* $0 < \mu < \rho < 1$. *Occupational employment share change and mean wage growth rate are increasing in skill intensity implied by* $\beta_j$ *and do not depend on the wage structure. There exists a combination of disutility parameters* $d_j$ *and skill intensity parameters* $\beta_j$ *so that employment share changes and mean wage growth implies polarization, i.e., higher growth of employment and*

[30] The formal definition of equilibrium and the key equilibrium relationships of the model is provided in Online Appendix section A.3.

*mean wage at the tails of wage structure relative to middle.*

I provide the formal proof in the Online Appendix Section A.3 and an intuitive discussion here. The economic forces shaping the reallocation of employment and the wage growth easily fit in the framework of SBTC. Suppose as in the canonical SBTC model that technical change is faster for high-skill worker and that different types of skills are gross substitutes in task production. Then demand increases towards the input which becomes relatively more efficient, and consequently the relative wages of high-skill workers increase. This is the relative demand force in the canonical SBTC model. In order for skill demand to translate into demand for skill-intensive occupations a further assumption should be made on the substitutability of tasks in the production of output. If elasticity of substitution across tasks in the production of final output is larger than the elasticity of substitution between skills in task production, then the demand for more skill-intensive occupation also rises more since that occupation produces at relatively increased level of efficiency thanks to the specialization towards more skilled workers. Therefore both the price of high-skill type and the task price of skill-intensive occupations increase. This translates into higher growth of mean occupational wage in skill-intensive occupations since the equally rising skill premium is reflected more heavily due to a greater share of high-skill workers. Here the key parameter is skill intensity, hence these results hold under any wage structure.[31]

The model does not strictly imply polarization. However, it is possible to observe the non-monotonic pattern along occupational mean wages if occupations with the lowest skill intensity are positioned in the middle of wage distribution. As discussed in the Online Appendix Section A.3, the wage structure is given by a combination of disutility and skill intensity parameters. If the disutility parameters are low enough for jobs of moderate skill intensity, that is they welcome high-skill workers more than many other occupations while they are not among the least desirable ones, then the wage structure is subject to polarization of employment share changes and mean wage growth.

## IV.C. Important Implications of the Model

In this section I discuss implications of the model on the relative demand for skills, and on alternative sources of occupation growth. First, I discuss the implications on the college wage premium estimation and suggest a flexible way of estimating the relative demand for skills. Then, I assess the consequences of potentially changing relative skills requirements and the secular rise in the relative supply of skills.

[31] Note that same qualitative results of the proposition hold under the alternative symmetric assumption such that $\frac{A_{Lt}}{A_{Ht}}$ grows and $\rho < \mu < 0$. Since the paper is not explicitly about modeling skills in the production function but concerned with the direction of the relative demand growth, I simply follow the SBTC literature in this assumption.

It is possible to derive the aggregate skill premium that nests the equation suggested by the canonical SBTC model. The skill premium equation is given by the ratio of economy-wide high-skilled wages to low-skilled wages both of which are calculated as the mean wage for the corresponding skill group weighted by occupations' employment share. Using the first order conditions of optimal task production the aggregate skill premium equation can be expressed as follows:

(7) $$\log\left(\frac{w_{Ht}}{w_{Lt}}\right) = \log\left(\frac{\beta_1}{1-\beta_1}\right) + \mu\log\left(\frac{A_{Ht}}{A_{Lt}}\right) + (\mu-1)\log\left(\frac{H_t}{L_t}\right) + \Gamma_{HLt},$$

where $\Gamma_{HLt} = (\mu-1)\log\left(\frac{\alpha_{H1t}}{\alpha_{L1t}}\right) + \log\left(\frac{\alpha_{H1t}+\left(\frac{d_2}{d_1}\right)\alpha_{H2t}+\cdots+\left(\frac{d_J}{d_1}\right)\alpha_{HJt}}{\alpha_{L1t}+\left(\frac{d_2}{d_1}\right)\alpha_{L2t}+\cdots+\left(\frac{d_J}{d_1}\right)\alpha_{LJt}}\right)$, and $\alpha_{Sjt} = \frac{S_{jt}}{S_t}$ for $S = \{H, L\}$.

The skill premium equation resembles that of the canonical model in terms of the two forces that is expressed as the race between education and technology after Tinbergen (1974), namely the relative growth of skill-specific technology (relative skill demand), and changes in relative skill supply. The evolution of skill premium differs from the canonical model because of the last term on the right hand side ($\Gamma_{HLt}$). It captures that in the occupation-based SBTC model there are two additional potential sources which can affect the aggregate skill premium. First is the changes in the ratio of high- to low-skill employment in each occupation, second is the changing representation of relative skills across occupations. These are directly related to the extensions this model has over the canonical one. Consequently, equation (7) is identical to canonical SBTC model if skill intensity parameter $\beta$ and disutility parameter $d$ are identical across occupations.

If within-occupation SBTC model is the correct one, then the OLS estimation of (7) suffers from the correlation of both relative demand and supply of skills with the error term which includes $\Gamma_{HLt}$. The extended SBTC model suggests the following form of the college wage premium equation:

$$\log\left(\frac{w_{Hit}}{w_{Lit}}\right) = \log\left(\frac{\beta_i}{1-\beta_i}\right) + \mu \log\left(\frac{A_{Ht}}{A_{Lt}}\right) + (\mu - 1)\log\left(\frac{H_{it}}{L_{it}}\right). \tag{8}$$

Results of the estimation of the canonical wage premium equation by Katz and Murphy (1992) and by extended model are provided in Table VI. Panel A shows the results for the canonical model.[32] The coefficient on the relative supply in column (1) suggests an elasticity of substitution of 1.61 and the time trend coefficient reports an annual relative demand growth of 3.1 percent for 1964-1987 period, which are remarkably similar to the results of similar regression models in the literature.

In Panel B results from the estimation of occupation-based model are presented. The occupation classification is restricted to two occupation groups, high- and low-wage/skill occupations, due to limitation imposed by CPS samples that do

[32]A novelty of Table VI is the choice of hourly wages instead of weekly earnings used by Katz and Murphy (1992) and others. See Online Appendix Section A.1 for details of data construction.

not allow for enough cells in each year to produce composition adjusted wage and supply variables for more detailed occupation groupings.[33] The use of two group of occupations is also supported by the observation that the most remarkable skill intensity differences are between upper and lower half of the occupational wage distribution. Estimation of equation (8) for 1964-1987 period in column (4) indicates a higher substitutability between skill types within occupations with an elasticity estimate of 6.6 $(1/0.15)$.[34] The estimated annual trend growth is 1 percent.

What is perhaps more surprising than different point estimates given by the disaggregate estimation is its implication on the evolution of the relative demand for skills. The canonical model's suggested path for the relative skill demand indicates a significant deceleration after 1992 (Goldin and Katz, 2008; Acemoglu and Autor, 2012). The post-1992 slowdown in relative demand is also confirmed by the data used here. Results of college premium regressions for the 1964-2014 period in Panel A column (2) report unstable coefficients for the relative supply and trend. The time-trend $\times$ post-1992 period interaction in column (3) indicates a statistically significant decline in the demand. However, a falling relative demand for high-skill

[33]The high-wage/skill group includes professional, managerial, financial, sales, production, and crafts workers. Transport, construction, mechanics, operator, assembler and service occupations are the low-wage/skill group.

[34]In particular, I estimate the following model

$$\log\left(\frac{w_{Hit}}{w_{Lit}}\right) = \psi_i + \mu \times timetrend + (\mu - 1)\log\left(\frac{H_{it}}{L_{it}}\right) + u_{it},$$

where $\psi_i$ represents occupation dummies and $u_{it}$ is the error term. Technically the bias of supply coefficient could go in either direction depending on the correlations between demand and supply measures with the error term, but estimating higher substitutability within narrower occupation groups is intuitive.

workers at a decade when computers were being increasingly used at the workplace has been found puzzling, and viewed as a shortfall of the canonical model.

Panel B of Table VI suggests that the extended SBTC model can fix this issue. Column (5) extends the estimation in column (4) to the full sample. Point estimates under both columns are very close. Column (6) includes the post-1992 interaction term, which clearly rejects the potential weakening of relative skill demand.

The extended model further suggests an alternative way to estimate the relative skill demand that is free from time trend assumption on which most estimates in the literature relies on. The idea is to use year-specific effects to capture economy-wide level of demand instead of time trend. I estimate the following model:

$$\log\left(\frac{w_{Hit}}{w_{Lit}}\right) = \psi_i + \psi_t + (\mu - 1)\log\left(\frac{H_{it}}{L_{it}}\right) + u_{it}, \tag{9}$$

where $\psi_t$ represents time-specific effects. The coefficient on the relative skill supply estimated with the time-effects model is shown in column (7) of Table VI. The estimated year-specific effects with standard error bands for each year between 1964 and 2014 are plotted in Figure IV. The figure confirms both the suitability of time-trend assumption to capture technical change, and the absence of decelerating relative demand after 1990. The reported slope of the linear fit is multiplied by 100, hence corresponding to 1.07 percent annual growth rate of relative skill demand in the long run.

*Alternative Drivers of Occupation Growth*

The analytical framework suggests economy-wide skill-biased technical change together with time-independent skill intensity differences across occupations as the driver of occupation growth in the economy. However, obviously there are other sources within the model's framework that potentially affect the reallocation of employment and wage growth. First, the model can address the rise of the exogenous relative skill supply, which is an important part of the canonical model as a determinant of skill premium. In addition, in this model changes in the relative skill supplies have a distributional impact. Intuitively, when there are relatively more high-skill workers in the economy their allocation across occupations will be proportional to occupations' skill intensity parameter (Online Appendix equation (A.6)). As a result, the exogenous rise in the relative skill supply translates into higher productivity in occupations with higher skill intensity. This effectively has the same impact with SBTC in the model, hence both employment shares and mean wages change in favor of the relatively skill-intensive jobs. This alternative channel only strengthens the model's predictions on reallocation. On the other hand, similar to the canonical model, relatively more high-skill workers in the economy has a negative impact on the skill premium (equation (7)) as $\mu < 1$.

Second, although introduced as fixed in the model the skill intensity parameter $\beta_j$ can be subject to change. In this case, an additional impact comes from the alteration of the skill structure. Consequently, occupations which improve their place in the skill intensity ladder relatively grow in size and wages. The stability of the skill-intensity over time (shown in Online Appendix Figure A.10) suggests that this potential driver of occupation growth is very likely to have limited impact.

Online Appendix Figure A.11 simply summarizes the occupational information on the two channels. The figure plots the 1980-2010 log change in skill intensity ($\frac{H_j}{L_j}$) against 1980 wages (upper panel), and against 1980 skill intensity (lower panel). The evidence is in line with what is predicted by the model following an exogenous increase in relative skill supply while $\beta_j$ is fixed for all occupations. The absolute change in skill-intensity is expected to be higher for more skill-intensive occupations while percentage changes should be similar to keep the relative skill intensities constant. As a result, the log change in skill intensity should be a flat line with positive intercept regardless of how occupations are ranked. Local means of actual changes in skill intensity shown in the figure roughly follow a constant trajectory both by wages and skills.

## V. Conclusion

In this paper, I argue that occupational employment and wage growth trends in the US imply different patterns depending on the type of the metric for skills. The post-1980 labor market polarization observed by wages disappears when the skill measure used is based on education, cognitive ability, and training requirements. Instead, the occupational employment demand change fits better to a pattern where it continuously and consistently favors relatively skill-intensive jobs, suggesting that the current extrapolation of labor market polarization onto the occupational skill space can be misleading.

I suggest an extension of the canonical SBTC model to occupations that can explain the skill-biased shifts of employment demand. When occupation-specific working conditions affect wage determination in addition to general skills the model can also help understanding part of polarization phenomena. Skill-biased occupation growth explored in this study does not necessarily rule out the existing explanations of polarization based on occupation-specific demand shifters, namely institutional changes, routinization, international trade, and structural change. My results emphasize the importance of the high-skill worker in the changing structure of labor market even for jobs placed low in the job quality ladder. A key message of the paper is that labor market polarization does not contrast with the growing demand for general skills in the labor market but rather happens somewhat by virtue of it. Results are encouraging for future research, and potentially policies, on the connection between wage inequality and tasks from the perspective of working conditions, and on the task-specific determinants of observable skill intensity differences across occupations.

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## TABLE I

Employment Share Change and Mean Real Wage Growth in Major Occupation Groups, 1980-2010, Occupations Ordered by Mean Wage

| | College | Noncollege | All | Predicted |
|---|---|---|---|---|
| *Panel A. $\Delta$ Employment Share $\times$ 100* | | | | |
| Managers/professionals/technicians/ finance/ public safety | 3.10 | 2.33 | 11.94 | 11.80 |
| Production/Craft | -1.41 | -1.86 | -2.25 | -4.27 |
| Transportation/construction/ mechanics/mining | -1.16 | -0.15 | -4.39 | -4.57 |
| Machine operators/assemblers | -1.95 | -8.97 | -7.29 | -6.17 |
| Clerical/retail sales | -2.61 | -1.29 | -2.71 | -0.03 |
| Service | 4.02 | 9.95 | 4.70 | -1.19 |
| *Panel B. Mean Wage Growth $\times$ 100* | | | | |
| Managers/professionals/technicians/ finance/ public safety | 27.53 | 18.39 | 29.02 | 30.33 |
| Production/Craft | 10.38 | 2.43 | 6.56 | 6.93 |
| Transportation/construction/ mechanics/mining | 3.79 | -0.88 | 1.18 | 6.51 |
| Machine operators/assemblers | 6.65 | -0.35 | 3.38 | 4.16 |
| Clerical/retail sales | 19.25 | 14.44 | 18.87 | 13.11 |
| Service | 12.65 | 10.05 | 12.72 | 11.43 |

*Note:* Employment is measured as total hours worked times population weights. Employment share changes in the first three columns may not sum up to zero because of rounding. Wages are measured as real hourly wages. Mean of occupations' log wage change weighted by 1980 labor supply is reported for each major occupation group in Panel B. In the last column predicted changes are obtained by regressing the actual changes on the 1980 college worker share of the median occupation in each group.
*Source:* 1980 Census and 2010 ACS

TABLE II

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<br>(+) | 0.000<br>(+) | 0.000<br>(+) | 0.003<br>(+) | 0.003<br>(+) | 0.131<br>(+) | 0.000<br>(+) |
| Quadratic term | 0.004 | 0.576 | 0.574 | 0.186 | 0.212 | 0.567 | 0.299 |
| Suggested shape | $\bigcup$ | $\bigcup$ | $\bigcup$ | $\bigcup$ | $\bigcup$ | $\bigcup$ | $\bigcap$ |
| 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* | Wage | College Share | Years of Education | AFQT | GED | Training (DOT) | Training (O*NET) |
|---|---|---|---|---|---|---|---|
| Linear term (alone) | 0.074<br>(+) | 0.000<br>(+) | 0.000<br>(+) | 0.000<br>(+) | 0.000<br>(+) | 0.000<br>(+) | 0.000<br>(+) |
| Quadratic term | 0.005 | 0.005 | 0.049 | 0.910 | 0.682 | 0.93 | 0.002 |
| Suggested shape | $\bigcup$ | $\bigcap$ | $\bigcap$ | $\bigcap$ | $\bigcap$ | $\bigcap$ | $\bigcap$ |
| Extreme value? in the range? | YES | YES | YES | NO | NO | NO | YES |
| Quadratic shape test | 0.008 | 0.170 | 0.303 | - | - | - | 0.151 |

*Note:* 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.

## TABLE III

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 |

*Note:* 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 for skill variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses.

TABLE IV

Predicting Occupational Tasks with Wages, 1980

*(Dependent Variable: Percentile Ranking of Occupational Task Measures)*

| A. Lower Half of 1980 Wage Distribution | | | | | | |
|---|---|---|---|---|---|---|
| | Abstract | Manual | Routine | Time Demand | Cognitive Demand | Hazard |
| Wage | 0.14 | 0.48 | 0.12 | 0.59 | 0.86 | 0.64 |
| Percentile Rank | (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 | 0.86 | -0.27 | -0.56 | 0.81 | 0.65 | -0.63 |
| Percentile Rank | (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 |

*Note:* 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 for task variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses.

TABLE V

Working Conditions Wage Premium
*(Dependent Variable: Log Real Hourly Wages)*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Working Conditions Index | 0.0191 | 0.0176 | 0.0189 | 0.0175 |
| | (0.0042) | (0.0044) | (0.0041) | (0.0044) |
| Abstract Intensity | | 0.0033 | | 0.0031 |
| | | (0.0029) | | (0.0029) |
| Routine Intensity | | 0.0026 | | 0.0025 |
| | | (0.0016) | | (0.0016) |
| Manual Intensity | | 0.0018 | | 0.0019 |
| | | (0.0034) | | (0.0034) |
| Working Conditions Index × | | | | |
| Cognitive Skill | | | 0.0050 | 0.0048 |
| | | | (0.0037) | (0.0037) |
| Social Skill | | | -0.0009 | -0.0009 |
| | | | (0.0035) | (0.0035) |
| Cognitive Skill × Social Skill | | | -0.0021 | -0.0020 |
| | | | (0.0035) | (0.0035) |

*Note:* Table shows in each column the estimates from equation 2 using NLSY-1979 data. All variables are standardized to have zero mean and unitary standard deviation. There are 89,789 observations and 10,323 workers in each specification. Each column includes dummy variables for workers, years, division, metro and urban status, 23 broad occupations, 3 digit industries, age, years of education, and the interaction of age and education dummies. See the text for information on task variables. Standard errors clustered by individual workers are in parentheses.

TABLE VI

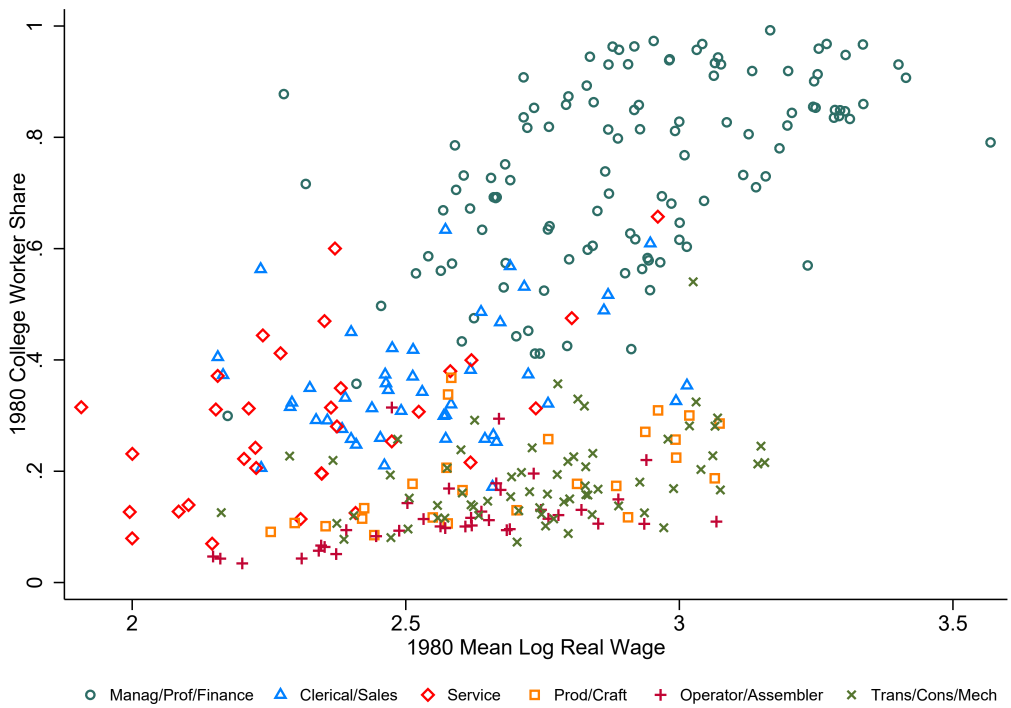
College-High School Log Wage Gap Estimations, 1964-2010
*(Dependent Variable: College Wage Gap)*

| | A. Aggregate | | | B. Occupation-Based | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Relative supply | -0.62 | -0.28 | -0.45 | -0.15 | -0.16 | -0.14 | -0.12 |
| | (0.14) | (0.04) | (0.07) | (0.04) | (0.02) | (0.02) | (0.02) |
| Time trend | 0.31 | 0.16 | 0.24 | 0.10 | 0.12 | 0.11 | |
| | (0.06) | (0.01) | (0.03) | (0.02) | (0.01) | (0.01) | |
| Time trend $\times$ post-1992 | | | -0.05 | | | 0.02 | |
| | | | (0.02) | | | (0.01) | |
| Constant | -0.52 | -0.06 | -0.30 | | | | |
| | (0.19) | (0.05) | (0.09) | | | | |
| Observations | 24 | 51 | 51 | 48 | 102 | 102 | 102 |
| $R^2$ | 0.61 | 0.95 | 0.96 | 0.88 | 0.96 | 0.96 | 0.99 |

*Note:* Table shows the coefficients estimated by OLS from the regression of college-high school log wage gap on relative skill supply and time variables. Relative wages and skill supply are calculated following the methodology of Goldin and Katz (2008). Hourly real wages are used. The data source is CPS. Columns at Panel B include occupation dummies. (7) includes year dummies. Robust standard errors are in parentheses.

FIGURE I

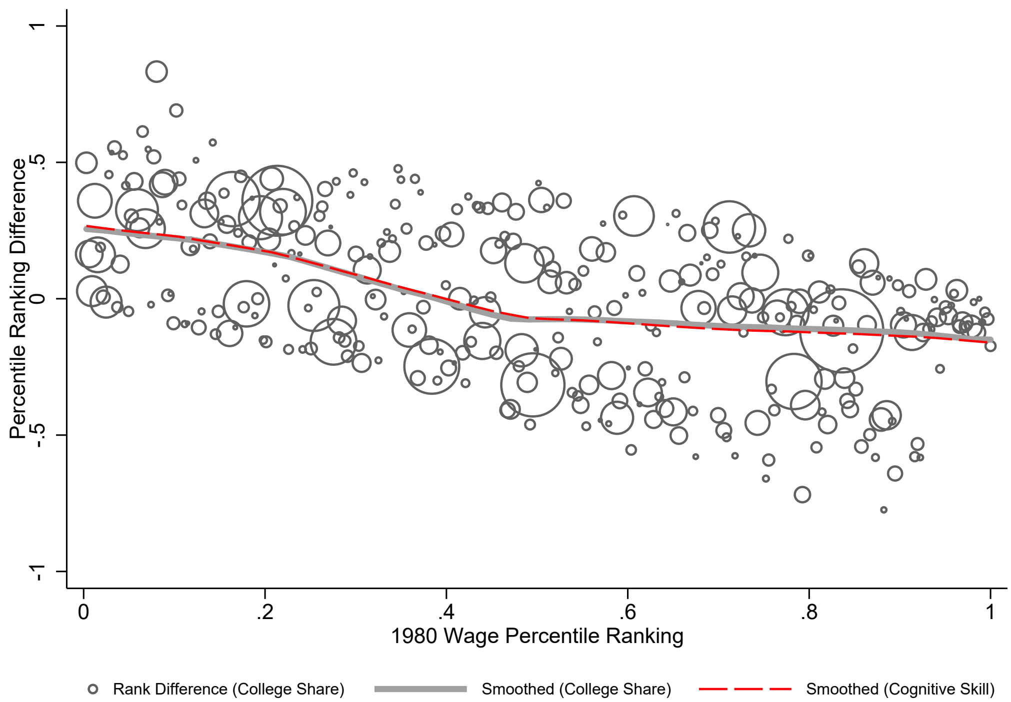
Occupational Skill Intensity and Wage Structure




*Note:* The figure 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.
*Source:* 1980 Census

FIGURE II

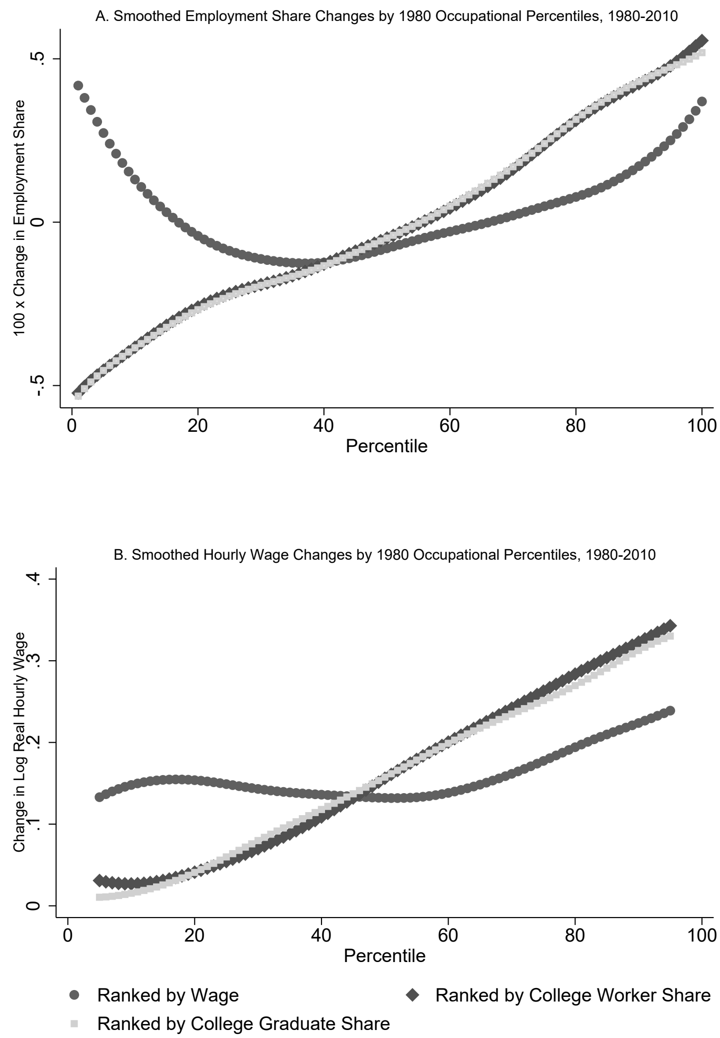
Skill-Wage Disconnect at Low-Wage Occupations




*Note:* The figure 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 by occupational AFQT score along wage percentiles. Smoothing is done by local polynomials using employment weights. See the data section on occupational AFQT scores.
*Source:* 1980 Census and NLSY-1979

FIGURE III

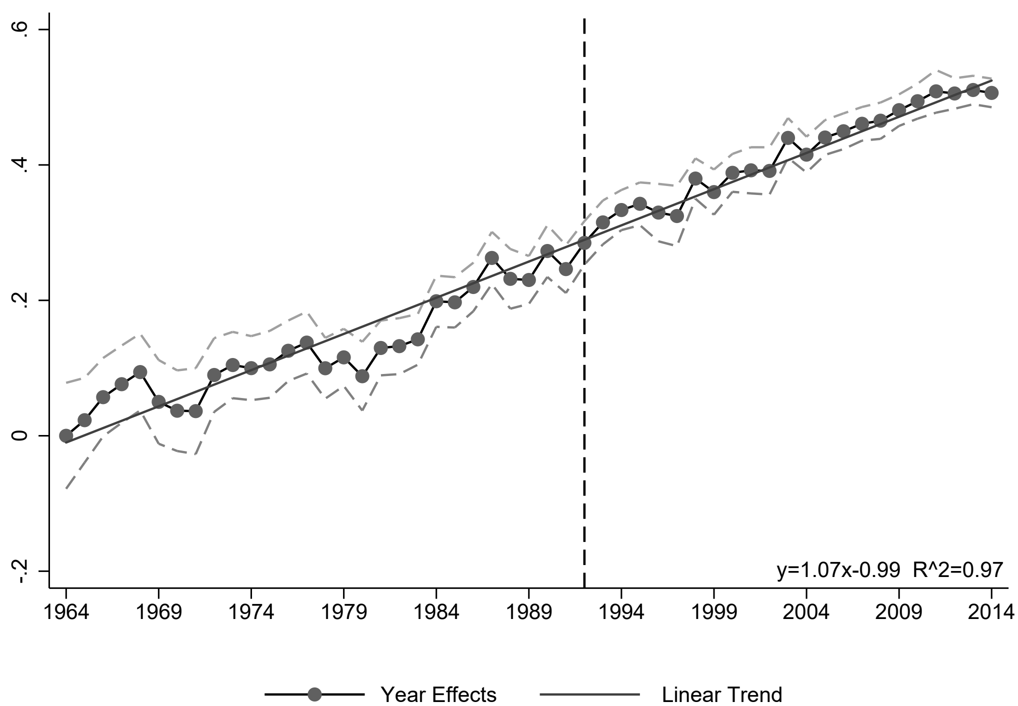
## Trends in Employment and Wage Growth




*Note:* 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 comes 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.

FIGURE IV

EVOLUTION OF THE RELATIVE DEMAND FOR SKILL IN THE US




*Note:* Figure shows point estimates and the standard error band of time dummies from the college wage premium equation reported in Table VI column (7). The coefficients are normalized to be equal to zero in 1964. Vertical dashed line marks 1992 for which the canonical model predicts a slowdown in the growth of relative skill demand.

# Supplementary Material

# Online Appendix for

# SKILL-BIASED OCCUPATION GROWTH

**Orhun Sevinc**

## A.1. Data Appendix

In this appendix section I describe the data treatment on Census and CPS samples used in the paper.[1]

### A.1.1. Census and ACS

The Census data cover 1980, 1990, 2000 Census 5% extracts, 2005 and 2010 surveys of ACS. 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.

[1] Census and CPS data are obtained from the IPUMS database (Steven Ruggles and Sobek, 2017).

### A.1.2. CPS

The data used is Annual Social and Economic Supplement of CPS for the period 1964-2014. The sample used in the paper is restricted to workers of age 18-64, 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 individuals with wages smaller than the first percentile of wage distribution are dropped.

Calculation of mean wages for skill groups, and skill supplies is subject to demographic and occupational adjustment. In order to use in aggregate estimations, in each year I construct demographic cells that are combinations of 2 gender, 5 education, 6 age groups. For occupation-based estimations, I generate each year-gender-education-age cell within 2 occupation groups. Long-run average cell sizes are used as fixed weights.

High-skill (college worker) wages are computed as fixed-weighted annual mean of log real wages for workers having 4 years of college education or more. Low-skill wages are fixed-weighted annual mean of log real wages for workers who are high school graduates without any college education.

High-skill supply is the sum of efficiency units for each demographic cell over all cells of workers with at least some college education. Efficiency units of each cell are total labor supply weights times average real wages for 4 years or more college, and a half of it for some college group. Low-skill supply is the sum of efficiency units for each demographic cell over all cells of workers with at most some college education. Efficiency units of each cell are labor supply weights times average real wages for high school graduates and below, and a half of it for some college.

## 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*.[2] 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. Nev-

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

ertheless, 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.IX 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.

### 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, Katz and Kearney (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, Katz and Kearney (2008).

The main practical difference between my paper and the two papers documenting polarization along education percentiles is the occupational classification. Autor, Katz and Kearney (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, Katz and Kearney (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, Katz and Kearney (2008) on the basis of *occ1990dd* instead of *occ1990*.

Figure A.X shows the smoothed employment share changes according to two different occupation codes. The upper panel replicates Autor, Katz and Kearney (2006) and Autor, Katz and Kearney (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.IX, the striking contrast may seem puzzling. For this reason, I compare two coding schemes based on their stability of occupation coverage in Autor, Katz and Kearney (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.XI 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, Katz and Kearney (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, Katz and Kearney (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. Equilibrium and Key Relationships

*Equilibrium*

An equilibrium at time $t$ is defined by allocations of the labor of each skill group across occupations $\{S_{jt}\}_{j=1}^{J}$, and the consumption choices of workers of each skill type $\{C_{Sjt}\}_{j=1}^{J}$, occupational wages for each skill group $\{w_{Sjt}\}_{j=1}^{J}$, and prices of task output $\{p_{jt}\}_{j=1}^{J}$ given fixed occupation weights in final output production $\{\gamma_j\}_{j=1}^{J}$, high skill weight in task production $\{\beta_j\}_{j=1}^{J}$, occupation-specific disutility parameters $\{d_j\}_{j=1}^{J}$, skill supplies $H_t$, $L_t$ and skill-specific productivity $\{A_{Ht}, A_{Lt}\}_{j=1}^{J}$ such that:

1) Workers choose the occupation that yields the highest utility.

2) The representative firm of final output optimally chooses the task input $T_{jt}$ for each occupation $j$, and task producers in each occupation optimally choose high-skill ($H_{jt}$) and low-skill ($L_{jt}$) labor input.

3) Occupational wages clear the labor market so that $H_t = \sum_{j=1}^{J} H_{jt}$ and $L_t = \sum_{j=1}^{J} L_{jt}$.

4) All output is consumed so that $\sum_{j=1}^{J} (H_{jt}C_{Hjt} + L_{jt}C_{Ljt}) = Y_t$

*First Order Conditions and Key Relationships*

Final good firm's optimal demand from occupation $j$:

(A.1)
$$\gamma_j {T_{jt}}^{\rho-1} {Y_t}^{1-\rho} = p_{jt}.$$

Optimal input demand for skill $H$ of the task producer in occupation $j$:

$$p_{jt}\beta_j{}^{1-\mu}A_H{}^{\mu}H_{jt}{}^{\mu-1}T_{jt}{}^{1-\mu} = w_{Hjt}. \tag{A.2}$$

Optimal input demand for skill $L$ of the task producer in occupation $j$:

$$p_{jt}(1-\beta_j)^{1-\mu}A_L{}^{\mu}L_{jt}{}^{\mu-1}T_{jt}{}^{1-\mu} = w_{Ljt}. \tag{A.3}$$

Working in some occupations yields lower utility. Therefore in an equilibrium where a positive level of employment exists in each occupation, workers should be indifferent between occupations. This implies that differences in disutility should be compensated by wage:

$$\frac{w_{Sjt}}{d_j} = \frac{w_{Sj't}}{d_{j'}}. \tag{A.4}$$

Equation (A.4) suggests that conditional on skill-type $S = \{H, L\}$ the wage ordering is given by disutility parameters. On the other hand, occupational wage structure (employment-weighted average of wages in each occupation) is not independent from the skill specialization of occupations. An occupation can offer lower wages compared to another one in both skill types but the average wage can still be higher because of the share of high-skill workers.[3] This can be seen by comparing the mean wages in two arbitrary occupations:

(A.5)

$$\frac{w_{jt}}{w_{j't}} = \frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hjt} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Ljt}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} = \left(\frac{d_j}{d_{j'}}\right) \left( \frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hj't} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Lj't}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} \right),$$

where $w_{jt}$ is the mean occupational wage calculated as the employment-weighted average of the wages of skill-types in an occupation. The second part of the equation is derived using the wage indifference condition (A.4). From equation (A.5) it is clear that less desirable working conditions increase the average wage, and the relative share of high-skill workers is another determinant. For instance, a less demanding job on average could yield higher wages compared to a job with more challenging attributes if it is sufficiently more skill intensive. Hence, the wage structure of occupations depend on the skill structure too.

Another implication of the model on occupational wage structure is related to its stability. Inspection of equation (A.5) also suggests that relative wages are affected by the increase in high-skill wage premium. Therefore it is possible to have significant changes in the wage structure as the premium rises since skill intensity across occupations are different.

[3] I implicitly assume here a higher relative wage for the high-skill worker in each occupation. This can be given by assuming a level of relative technology $\frac{A_{Ht}}{A_{Lt}}$ that is sufficiently low or high depending on the sign of $\mu$.

The model's implication on the skill structure, however, is relatively straightforward. Using the indifference condition and the first order conditions of task production for each occupation and skill type the following is derived:

$$\frac{\beta_j}{\beta_{j\prime}} \frac{(1-\beta_{j\prime})}{(1-\beta_j)} = \frac{H_{jt}}{H_{j't}} \frac{L_{j't}}{L_{jt}}. \tag{A.6}$$

Equation (A.6) implies that the relative skill intensity hierarchy across occupations is constant. The supply of skills $H_t$ and $L_t$ might be subject to change, yet this is never translated into a change in the relative skill intensities. Furthermore occupations' skill structure is pinned down simply by $\beta$s independent of the occupations' wage. Given a set of skill intensity parameters the equation predicts a stable occupational skill structure.

In fact the model's prediction for stable skill structure and potentially changing wage structure is confirmed by the long-run comparison of occupational rankings based on average wages and share of high-skill worker in Figure A.X. Occupational wage ranking in 1980 is correlated to ranking in 2010 although there is substantial change for some occupations. On the other hand, occupational ranking based on high-skill share looks quite stable in the long-run.

### A.3.2. Proof of Porposition 1

In this appendix section I show the existence and uniqueness of the equilibrium solution of the model and provide the proof of the claims in proposition 1. The case with $J = 3$ is sufficient to prove all parts of the proposition. Therefore without loss of generality I study the economy with three occupations. Generalizing the proof for $J > 3$ number of occupations is straightforward. First, I show that there exists a unique equilibrium allocation of labor across occupations in the model. Secondly, I show that under the assumptions in proposition, the occupations' employment growth is proportional to $\beta_j$. Then, I show that occupational mean wage growth is monotonically increasing in $\beta_j$. Lastly, for the labor market polarization result I construct a case which illustrates that polarization of employment and wages can be obtained as the model's outcome.

Before the proof of the proposition, I first show the existence of the unique equilibrium in terms of employment allocations of each skill type across occupations. Combining the first order conditions for optimal task choice, and optimal skill type demand the following can be derived for relative share of employment of skill-type $H$ in two arbitrarily chosen occupations $j$ and $j'$:

$$\left(\frac{h_{jt}}{h_{j't}}\right)^{(1-\rho)} = \left(\frac{d_{j'}\gamma_j}{d_j\gamma_{j't}}\right)\left(\frac{\beta_j}{\beta_{j't}}\right)^{(1-\rho)}\left(\frac{1-\beta_j}{1-\beta_{j't}}\right)^{\frac{\rho-\mu}{\mu}} \left(\frac{\left(\frac{\beta_j}{1-\beta_j}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right)^{\frac{\rho-\mu}{\mu}}, \tag{A.7}$$

where $s_{jt} = \frac{S_{jt}}{S_t}$ for $S = H, L$ denotes the employment share within the skill group.

The resource constraint on employment together with equation (A.6) implies the following for the ratio of high-skill worker to low-skill in occupation $j$:

$$\frac{H_{jt}}{L_{jt}} = \frac{H_t}{L_t}\left(a_{jj'} + (1-a_{jj'})\,h_{jt} + (a_{ji}-a_{jj'})\,h_{it}\right), \tag{A.8}$$

where $a_{mn} = \frac{\beta_m(1-\beta_n)}{\beta_n(1-\beta_m)}$ for two occupation index number $m$ and $n$; and $j$, $j'$, $i$ denote the three occupations.[4]

In order to characterize the equilibrium allocation, I plug (A.8) into (A.7) and express $h_{1t}$ as an implicit function of $h_{2t}$ from the comparison of occupations indexed as 1 and 3:

[4]Note that given relative skill supply in an occupation, relative skill supply for any other occupation can be obtained simply by equation (A.6).

$$h_{1t} = (1 - h_{1t} - h_{2t}) \left(\frac{d_3\gamma_1}{d_1\gamma_3}\right)^{\frac{1}{(1-\rho)}} \left(\frac{\beta_1}{\beta_3}\right) \left(\frac{1-\beta_1}{1-\beta_3}\right)^{\frac{\rho-\mu}{\mu(1-\rho)}}$$

$$\left( \frac{\left(\frac{\beta_1}{1-\beta_1}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{21}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_3}{1-\beta_3}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{21}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1} \right)^{\frac{\rho-\mu}{\mu(1-\rho)}}.$$

Let's assume that $\beta_1 > \beta_2 > \beta_3$. From the equation it can be verified that $h_{2t} = 1$ implies $h_{1t} = 0$; and $h_{2t} = 0$ implies $0 < h_{1t} < 1$. In this relation $h_{1t}$ can be found as the intersection of 45 degree line representing the left hand side and the curve given by the right hand side, treating $h_{2t}$ as exogenous. The left hand side is increasing in $h_{1t}$ and independent of $h_{2t}$. The right hand side is decreasing in both $h_{1t}$ and $h_{2t}$ since it is assumed that $0 < \mu < \rho < 1$. Therefore, a higher $h_{2t}$ is a downward shift of the right hand side and leads to a lower value for $h_{1t}$. Consequently, $h_{1t}$ is monotonically decreasing in $h_{2t}$ while $0 < h_{2t} < 1$.

In the same way, $h_{2t}$ can be written as an implicit function of $h_{1t}$ from the comparison of occupations indexed as 2 and 3. By symmetry, $h_{1t} = 1$ implies $h_{2t} = 0$; $h_{1t} = 0$ implies $0 < h_{2t} < 1$; and $h_{2t}$ is strictly decreasing in $h_{1t}$. The relations described in this and previous paragraph has a single intersection point within the assumed range of employment shares. Therefore there exists only one pair of $(h_{1t}, h_{2t})$ that satisfies both equations. Since $h_{3t}$ is given by $h_{1t}$ and $h_{2t}$, and $l_{1t}$, $l_{2t}$, $l_{3t}$ can be uniquely obtained using (A.8), within the unit square there exists a unique equilibrium allocation. Here the assumption on the ordering of the $\beta$s is not restrictive, for any other ordering the same argument holds after suitable adjustments in the occupation sub-indexes.

Now I move to proving that rising relative technology for high-skill workers implies reallocation of labor into more skill intensive occupations. Let's keep assuming that $\beta_1 > \beta_2 > \beta_3$. Then it follows that $a_{13} > a_{12} > 1$. First, consider the alternative case that $\frac{A_{Ht}}{A_{Lt}}$ rises and $\frac{h_{1t}}{h_{2t}}$ falls. By symmetry of (A.7), $\frac{h_{2t}}{h_{3t}}$ decreases too. From (A.8) it is clear that $\frac{H_{1t}}{L_{1t}}$ increases which, together with skill-biased technology growth, (A.7) implies that $\frac{h_{1t}}{h_{2t}}$ increases, contradicting the constructed case. Similarly, consider the other alternative that $\frac{h_{1t}}{h_{2t}}$ does not change following the change in technology. By symmetry, $\frac{h_{2t}}{h_{3t}}$ is fixed too. As a result $\frac{H_{1t}}{L_{1t}}$ is constant, and (A.7) implies a rising $\frac{h_{1t}}{h_{2t}}$, which is a contradiction. Therefore the new unique equilibrium allocation is consistent only with reallocation of high-skill labor into more skill intensive occupations, i.e., those with higher $\beta$. Equation (A.6) suggests that the same holds for low-skill employment. Hence, occupational employment growth and consequently employment share change is increasing in $\beta_j$.

The relative occupational mean wages at equilibrium can be shown in the following representation for two arbitrarily chosen occupations $j$ and $j'$:

$$\text{(A.9)}\quad \frac{w_{jt}}{w_{j't}} = \left[\frac{d_j}{d_{j'}}\right] \left[\frac{\left(\frac{H_{j't}}{L_{j't}}\right)+1}{a_{jj'}\left(\frac{H_{j't}}{L_{j't}}\right)+1}\right] \left[\frac{a_{jj'}\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right]$$

The part of the proposition on wage growth follows from the equation. The right-hand side of the equation is strictly increasing when $\beta_j > \beta_{j'}$ because second and third brackets increase when there is skill-biased technology growth. The term in the second bracket rises since $\frac{H_{j't}}{L_{j't}}$ falls and $a_{jj'} > 1$.[5] The last term in the brackets is also increasing since the numerator grows faster than denominator ($a_{jj'} > 1$).[6]

I end the proof by constructing a wage structure that enables employment and wage polarization along occupational wages. Since the relative employment and wage growth is entirely determined by the relative skill intensity, the construction aims to put the lowest $\beta_j$ occupation in the middle of the wage ranking. I construct the case such that $\beta_2 < \beta_1 = \beta_3$. Then the desired wage structure is obtained if $w_{1t} > w_{2t} > w_{3t}$. This is possibly the case for $d_1 > d_2 > d_3$ where $d_1$ is sufficiently large and $d_3$ is sufficiently low. Inspecting equation (A.9) for $j = 2$ and $j' = 1$ indicates that the last two term in brackets on the right-hand side are both bounded. The second term in brackets

[5]This follows (A.8) as a result of the reallocation of high-skill workers towards more skill intensive occupations.

[6]Note that growth of $\frac{A_{Ht}}{A_{Lt}}$ implies growth of $\frac{H_{j't}A_{Ht}}{L_{j't}A_{Lt}}$ in equilibrium for any occupation $j'$. This is given by the first part of the proposition and equation (A.7).

converge to 1 as the skill intensity goes to zero from above. The last term in brackets converges to $a_{21}$.[7] Hence, there exists $d_1$ high enough to ensure $w_{2t}/w_{1t} < 1$ for given time t. Similarly, inspecting equation (A.9) for $j = 2$ and $j' = 3$ shows that the last two term in brackets on the right-hand side are both bounded, and converge to 1 and $a_{23}$, respectively. Hence, there exists $d_3$ low enough to ensure $w_{2t}/w_{3t} > 1$ for given time t.

[7] This can be derived by applying L'Hôpital's rule while $\frac{H_{j't}A_{Ht}}{L_{j't}A_{Lt}}$ goes to infinity.

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## Table A.I

## 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 |

*Note:* 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 for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses.

Table A.II

## 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 |

*Note:* 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 for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses.

Table A.III

## Relationship between Tasks and Wages, 1980 Census

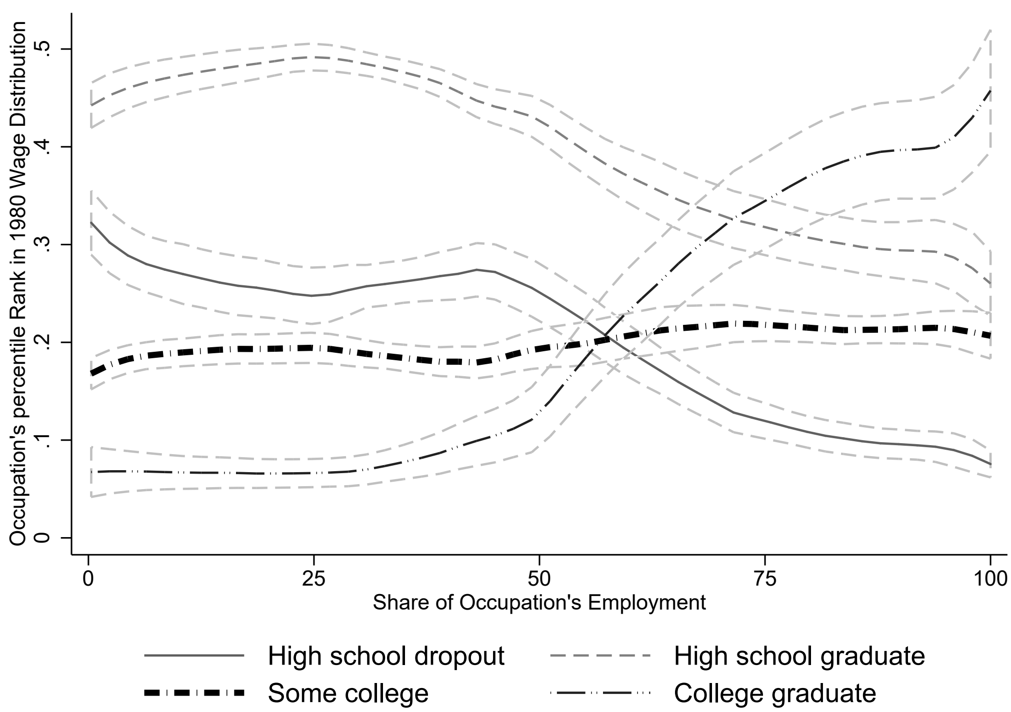
*(Dependent Variable: Log Real Wages, 1980)*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Mental demand | | 7.85 | 8.51 | 8.09 |
| | | (0.04) | (0.04) | (0.04) |
| Time demand | | 1.87 | 2.93 | 2.97 |
| | | (0.03) | (0.04) | (0.04) |
| Hazard | | 6.84 | 6.93 | 6.83 |
| | | (0.04) | (0.04) | (0.04) |
| RTI | -2.47 | | -0.94 | -0.54 |
| | (0.03) | | (0.03) | (0.03) |
| $RTI^2$ | 0.41 | | 0.53 | 0.43 |
| | (0.01) | | (0.01) | (0.01) |
| Observations | 4,120,949 | 4,120,949 | 4,120,949 | 4,120,949 |
| $R^2$ | 0.29 | 0.32 | 0.32 | 0.33 |

*Note:* Numbered columns show the coefficients estimated by OLS from the regression of Census 1980 individual wages on the corresponding task measure shown in the rows. RTI is the composite routinization measure from Autor and Dorn (2013). Columns (1) to (3) include controls for years of education, quartic of age, gender, race and metro status. Column (4) include controls for interactions of education, age, gender variables, and also race and metro dummies. All reported coefficients are multiplied by 100. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses.

Figure A.I

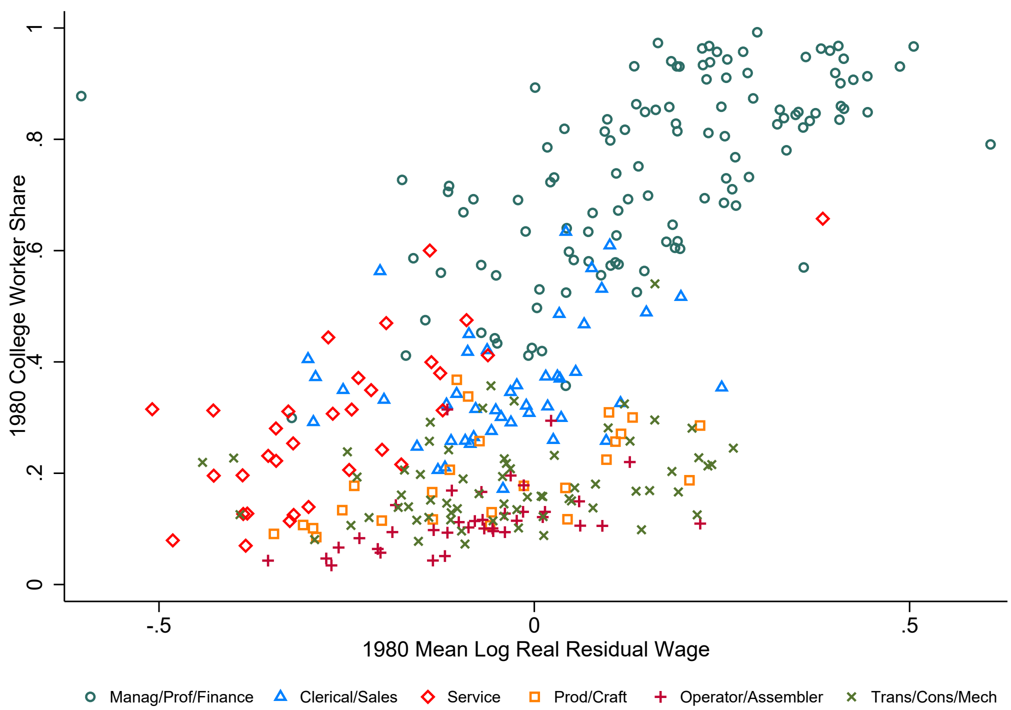
Smoothed Occupational Education Intensity by Wage Structure




*Note:* 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.II

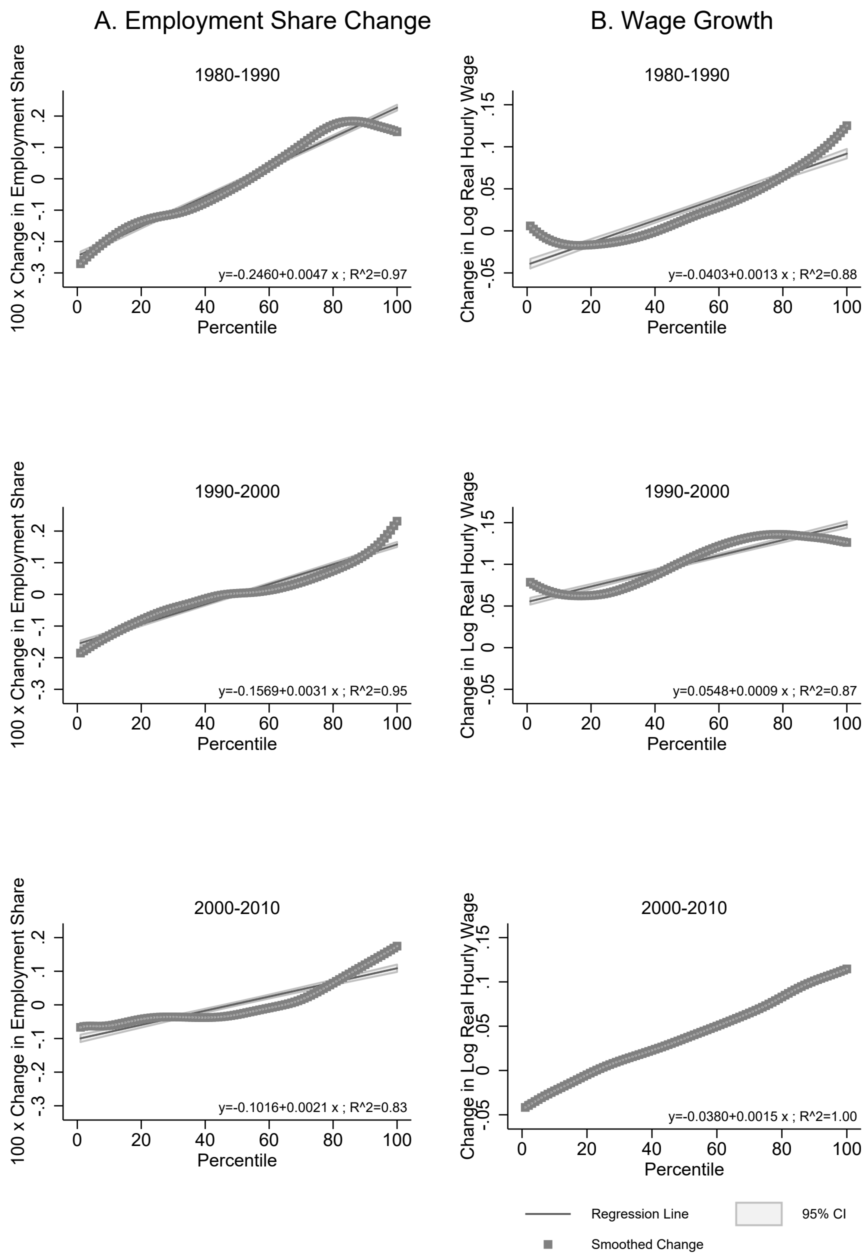
Occupational Skill Intensity and Residual Wages




*Note:* Residual wages are obtained from regressing 1980 Census individual 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.III

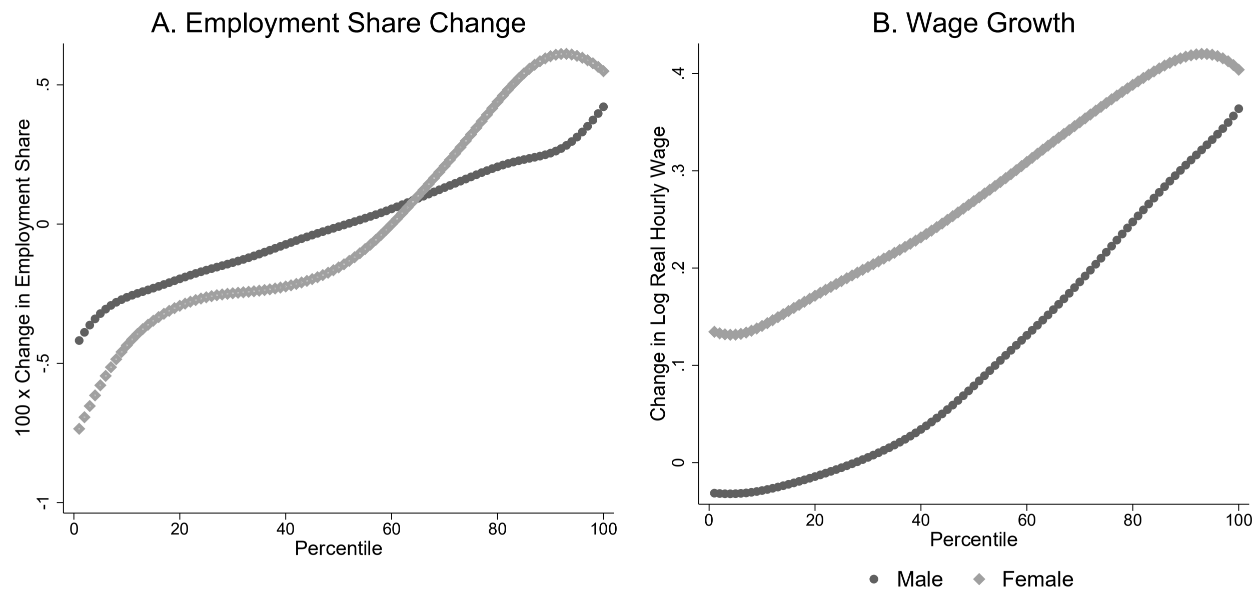
Smoothed Decadal Changes in Employment and Real Wages




Notes: The figure shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in occupational employment share of occupations 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.IV

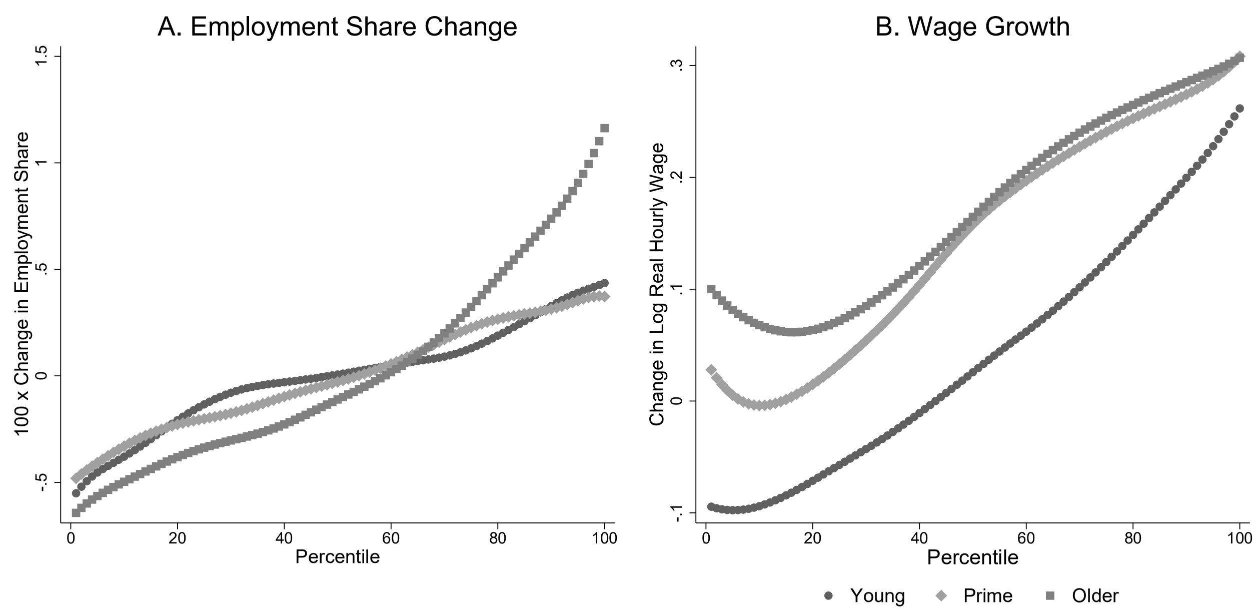
Monotonic Occupation Growth by Gender




*Note:* 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.

Figure A.V

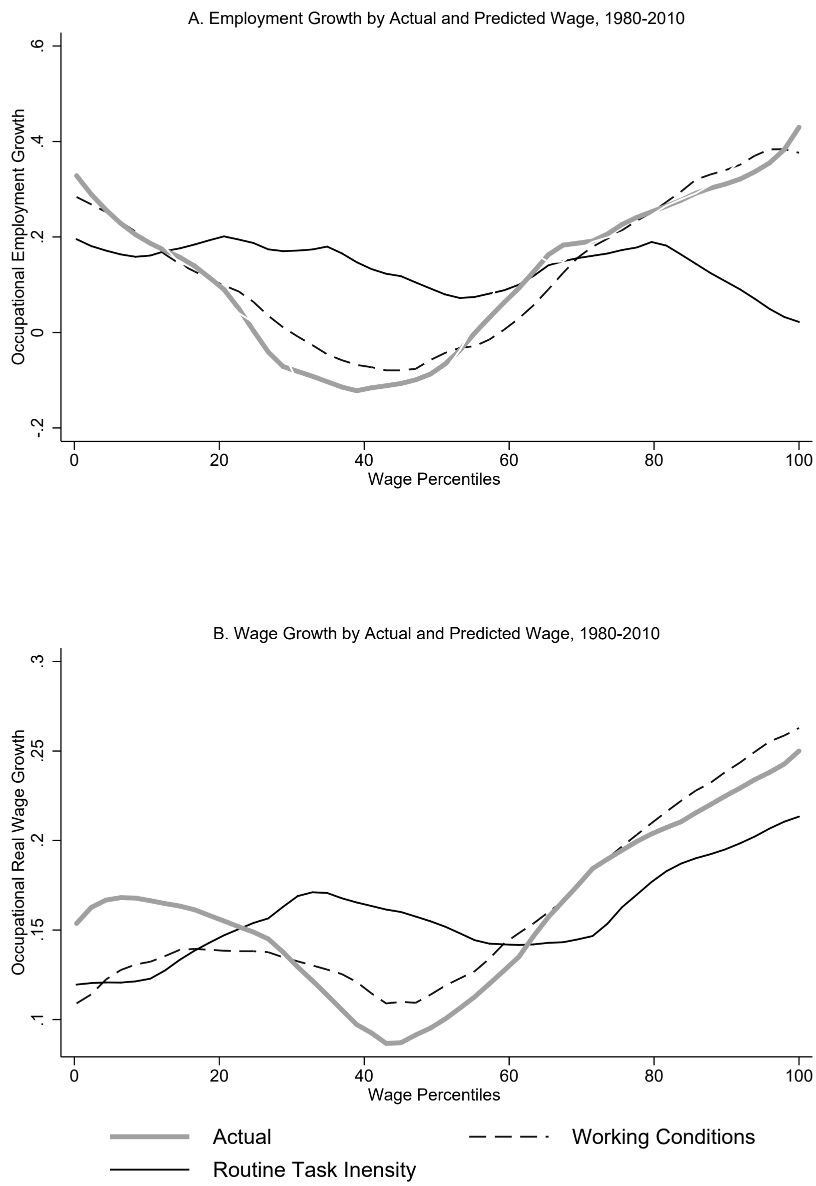
Monotonic Occupation Growth by Age




*Note:* 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.

Figure A.VI

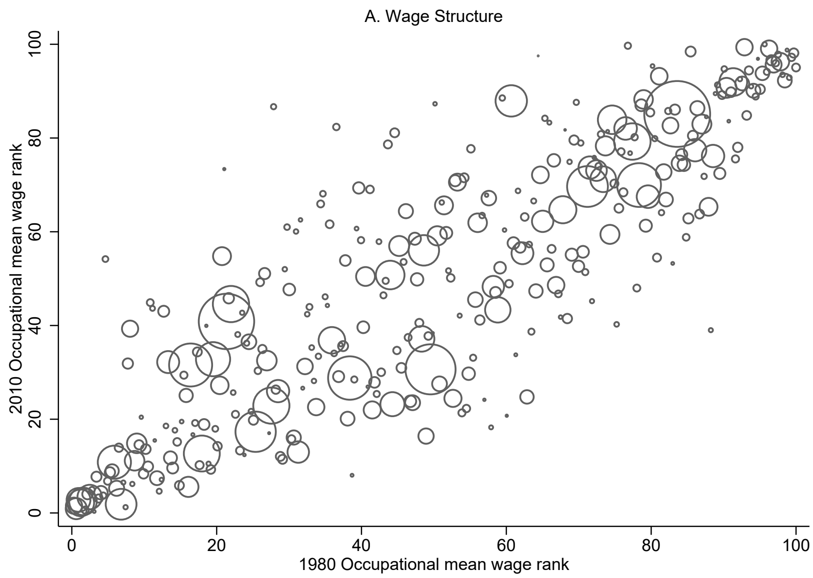
Smoothed Employment and Wage Growth by Actual and Predicted Wage Percentiles, 1980-2010




*Note:* Employment growth is the log change in total hours of an occupation between 1980-2010. Wage percentiles are percentile rankings of actual or predicted wages in 1980. Predicted wages by working conditions are obtained by the equation estimated in Table A.III column (4) using only the coefficients of time demand, mental demand, and hazard variables. Predicted wages by routine task intensity are obtained by the equation estimated in Table A.III column (4) using only the coefficients of RTI and its square. Smoothing is performed by local polynomials of degree 0 with bandwidth of 10 and weighted by 1980 occupational employment shares.

Figure A.VII

Wage and Skill Structure in the Long Run, 1980-2010

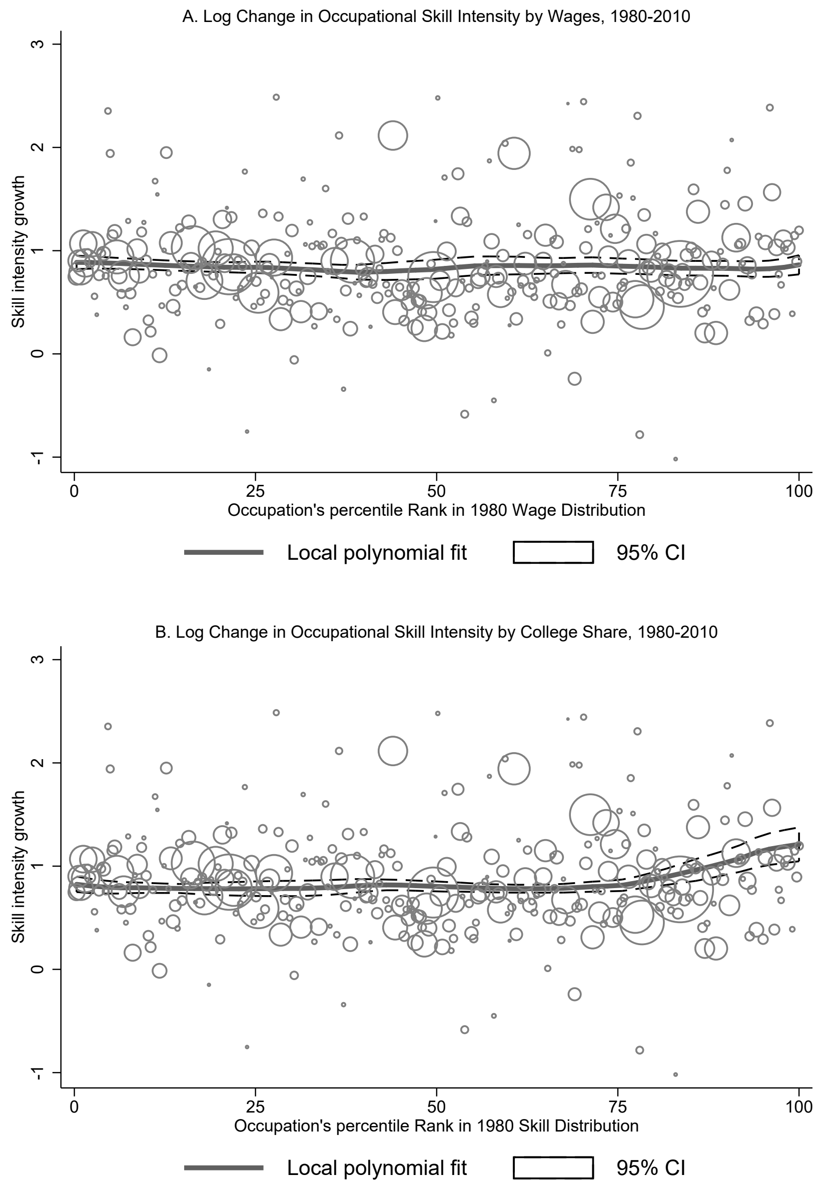




*Note:* The figure compares 1980 and 2010 wage and skill rankings of occupations. Mean wage ranks are calculated as the percentile rank of real mean log wages, and mean skill intensity rank is calculated as the percentile rank of mean college employment share. The size of each point is proportional to corresponding occupation's employment share.

Figure A.VIII

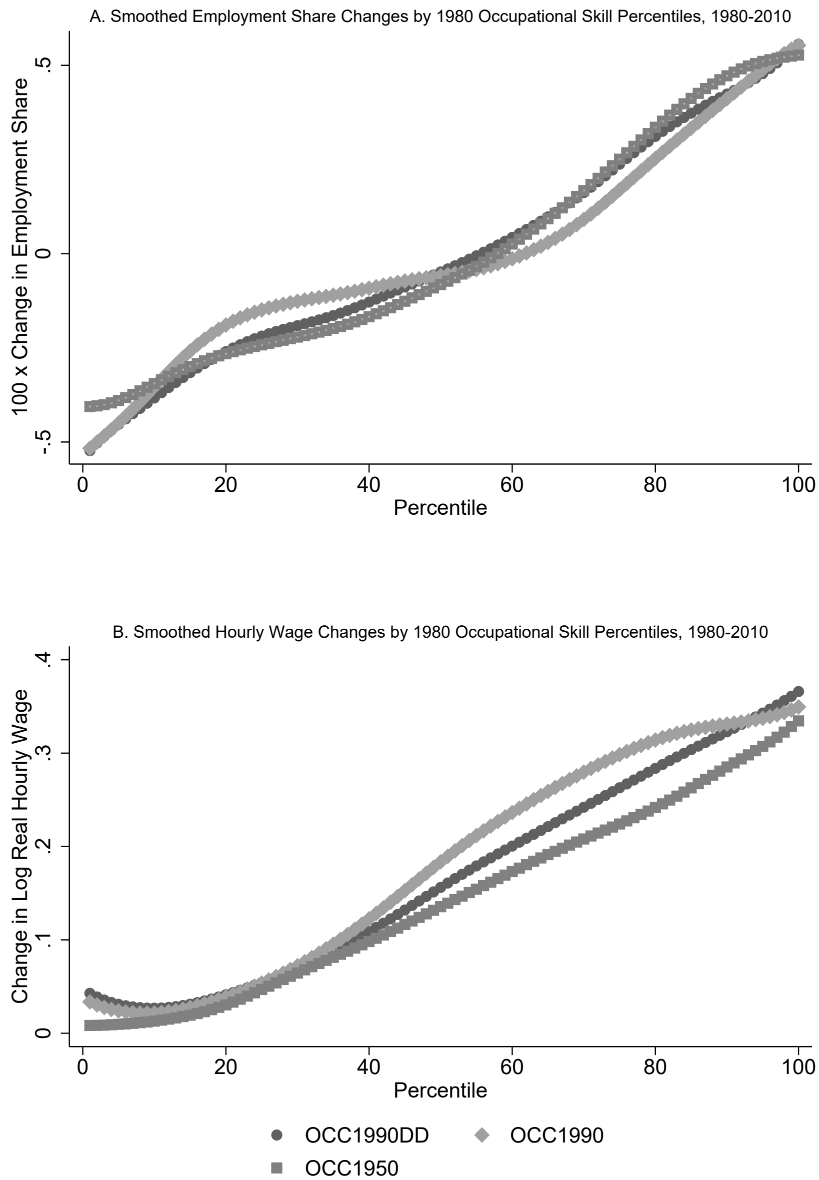
Change in Skill Intensity, 1980-2010




*Note:* The figure plots 1980-2010 change in the log of skill intensity by initial wages (Panel A) and initial skill intensity (Panel B). Skill intensity is defined as annual hours worked by college workers divided by annual hours worked by non-college workers in each occupation. Circle size is proportional to the employment share in 1980. Solid lines inside boxes show the smoothed mean relationship by a local polynomial using labor supply weight, surrounded by 95% confidence interval.

Figure A.IX

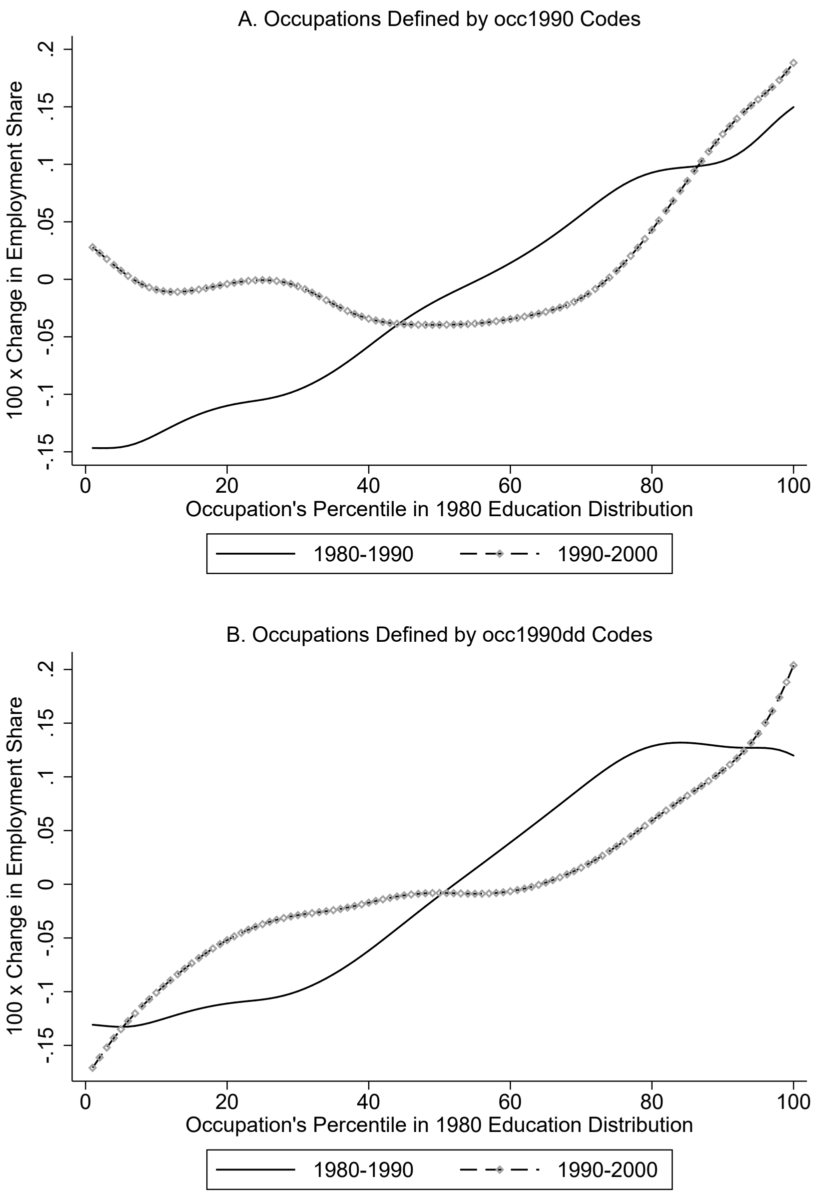
Monotonic Occupation Growth and Occupation Classification




*Note:* 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.X

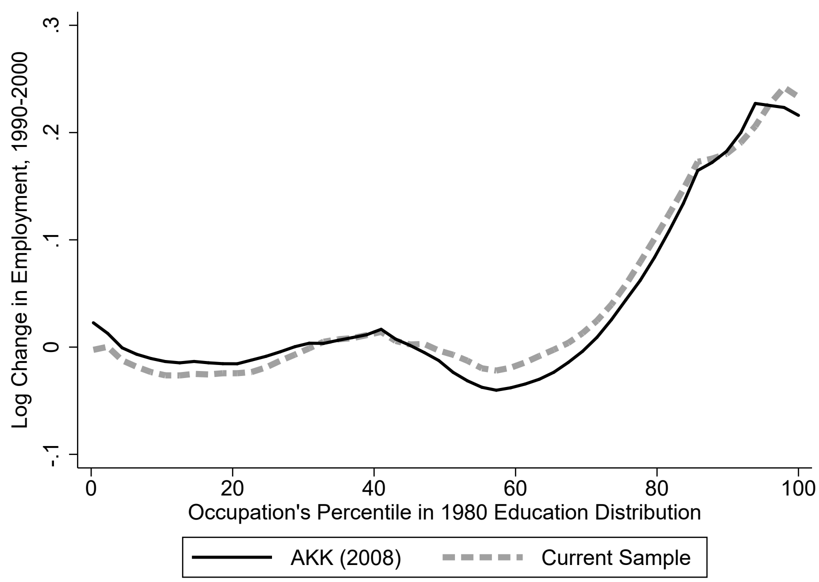
Smoothed Changes in Employment Share by Skill Percentile and Occupation Codes




*Note:* 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, Katz and Kearney (2008). *occ1990dd* occupation codes are merged to the original data by a crosswalk from Autor and Dorn (2013).

Figure A.XI

Smoothed Occupational Employment Growth of *occ1990* Occupations




*Note:* 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, Katz and Kearney (2008). Current sample indicates the data used in this paper.