Skill-Biased Technical Change and Labor Market Polarization: The Role of Skill Heterogeneity Within Occupations*

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Abstract

I document that employment share change and wage growth of occupations tend to increase monotonically with various measures of skill intensity since 1980 in the US, in contrast to the existing interpretation of labor market polarization along occupational wages. The observation is not particularly driven by a specific decade, gender, age group, or occupation classification. The evidence suggests that polarization by wages does not imply polarization of skills that have cross-occupation comparability. Skill-biased and polarizing occupation demand coexist as a result of the weak connection of wage and observable skill structure particularly among the low-wage jobs in the 1980. The empirical findings of the paper can be reconciled in an extended version of the canonical skill-biased technical change model which incorporates many occupations and within-occupation heterogeneity of skill types.

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1 Introduction

The task-based view in labor economics has had a profound impact on the way economists perceive inequalities in the labor market. Perhaps, this impact is most notable in our understanding of skill-biased technical change (henceforth SBTC), which has been a cornerstone in the wage inequality literature.[1] The canonical model of SBTC typically assumes skilled and unskilled workers in the economy where tasks and skills are implicitly equivalent (Katz and Murphy, 1992). The task perspective emphasizes the conceptual difference of work activities (tasks) from the set of productive worker capabilities (skills) (Acemoglu and Autor, 2011), and the practical importance of occupations as the unit of empirical analysis (Firpo et al., 2011).

One implication of the task perspective in the literature has been the development of a nuanced view on technical change, where recent advances in computer technology affect abstract, routine, and manual tasks in different ways (Autor et al., 2003). The resulting emphasis on occupations revealed an important aspect of labor market inequalities that the canonical model could not predict, namely labor market polarization referring to slower growth in employment and wages in middle-wage jobs relative to others located at the tails of the wage distribution.[2] 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 model (see, e.g., Autor et al., 2006; Goos and Manning, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013)

Untangling tasks from skills has proved itself as an empirically remarkable improvement over the canonical model, however both approaches still share a common assumption that strictly isolates skill-types in the performance of a given task. In other words, a task can only be performed by a single type of worker, either absolutely (as in the canonical model) or conditional on the state of technology (as in task-based models).[3] The aim of this paper is to relax this assumption and explore the role of occupational skill heterogeneity by providing a characterization of the evolution of

[1] See Goldin and Katz (2008) both for the empirical evidence on how the simple demand and supply framework of SBTC, which is referred to as the canonical model in Acemoglu and Autor (2011), can successfully help to understand the evolution of the labor market inequalities, and for a review of the literature on the SBTC.

[2] Polarization is shown to be a pervasive phenomenon both in the US (Autor et al., 2006, 2008; Autor and Dorn, 2013), the UK (Goos and Manning, 2007), and many other advanced economies (Goos et al., 2009, 2014). Barány and Siegel (2017) argue that polarization starts as early as the 1950s in the US. Polarization has been the most influential illustration of how the canonical SBTC model fails to explain trends of inequality at occupation level (e.g., Autor et al., 2006, 2008; Goos and Manning, 2007). See Acemoglu and Autor (2011) and Acemoglu and Autor (2012) for other evidence which cannot be explained within the canonical model.

[3] The existing task literature is well aware of skill heterogeneity within occupations (e.g., Goos and Manning, 2007). However, this is not reflected in the task-based models and explanations of inequality trends.

inequalities with respect to differences in observable skill intensities across tasks.

The motivation for this study can be summarized in Figure 1, which plots smoothed shares of skill groups in 1980 occupational employment by occupations' wage percentile ranking. The education shares of employment imply substantial heterogeneity within occupations when ranked by wages. All types of skills are found in significant shares in employment throughout the distribution with varying weights. Furthermore, from the lens of education intensities it does not seem realistic to characterize occupations throughout the wage distribution as high-, low- and middle-skilled. While the high school dropouts tend to have a higher share in employment towards the lower tail of the distribution, this group appears nowhere as the dominating skill component of jobs. Similarly, both high school graduates and workers with some college education, who can be considered as the middle-skill workers, do not show a drastic tendency to grow in the middle of the wage distribution compared to the lower tail.[4] Instead, there is a clear disconnect between education and wages for occupations below the median wage.

Figure 1 raises two important questions regarding the skill-based interpretation of the cross-occupation inequality trends. Can labor market polarization be consistently confirmed by skill measures other than wages? Are there any implications of within-occupation heterogeneity of skill types in the reallocation of employment across tasks and in the evolution of wages? While answering these questions this paper contributes to the existing literature in the following aspects.

The first contribution of the paper is to document that polarization observation in the long run is only limited to wage ranking of occupations in a set of available skill measures. When the skill measure used is the share of college workers in employment, which is the relevant variable for assessing the skill content according to SBTC hypothesis, occupational employment and wage changes follow a monotonic path proportional to occupational skills rather than a u-shape. Other education-based variables as well as measures of trainability and ability also suggest that employment and wage growth of occupations are proportional to skill intensity. The observed monotonic growth is broadly robust to the choice of occupation classification, prevails within each decade from 1980 to 2010, and holds within the labor market for each gender and age group.

The second contribution is a set of empirical observations that speak to the determinants of the documented contrasting patterns of inequality by wage and skill rankings and explore the connection

[4] There is no consensus in the task literature on the educational content of the middle-skill type. Acemoglu and Autor (2011) include both high-school graduates and workers with some college education while Autor and Dorn (2013) exclude the latter group of workers.

between the structure of occupational wages and skills in 1980. In order to understand what stands behind the observed mismatch between polarization and monotonic changes in task demand, I extend the evidence leading to Figure 1. Using a broad set of skill measures, I argue that occupational mean wage is not a good proxy of worker skills for jobs at the lower half of the wage distribution. In addition, occupational wages reflect other occupation-specific attributes such as how demanding the job is in terms of working time and cognitive processing capacity, and the level of exposure to hazardous conditions, better than acquired skills or education for the low-wage jobs in 1980. The data also reveals that distribution of skills by wages in broader occupation groups is beyond the stylized three-skill view that matches specific occupation groups to certain skill types. Remarkably, the so-called low-skill service occupations on average exhibit higher skills than many of the so-called middle-skill occupations along the wage distribution. Finally, I bring evidence showing that college workers are a significant part of lower skilled occupations and both college and non-college workers played a substantial role in the relative employment growth of bottom and top wage occupation groups.

Third contribution is to reconcile the first two set of findings. I present a simple extension of the canonical SBTC model to many occupations, which nests the skill premium equation of Katz and Murphy (1992), and show that the observed monotonic employment and mean wage growth is consistent with it. Furthermore, if the occupational wage structure does not solely depend on the mean observable skill intensity but other task-based attributes such as occupation-specific differences in preferences, the model is also qualitatively capable of explaining labor market polarization along wage distribution jointly with monotonic changes by skills.[5]

The most important element of the model is that low-skill and high-skill workers, though in different proportions, jointly contribute to the production of tasks in all occupations. The key mechanism to generate the labor demand forces is given by variation in SBTC-driven labor productivity growth across occupations and differences in the share of college to non-college workers. Hence, occupation-specific productivity growth drives labor reallocation as in models of structural change.[6] Having

[5]I illustrate a framework based on compensating differentials across occupations. Same qualitative results can also be motivated by a Roy-type occupation-specific productivity that is heterogeneously distributed across workers (see, e.g. Barány and Siegel, 2017). My modeling choice for compensating differentials is due to my observation that occupational wage structure can be better predicted by task attributes that are potentially associated with disutility from work (such as required hours of work for the job) compared to three task elements of routinization hypothesis. See Bryson and MacKerron (2016) for evidence on the negative impact of working on happiness. Authors also document that the negative impact is significantly lower for individuals at lower income levels. Bryson et al. (2012) presents direct evidence on the negative association of wages with worker wellbeing.

[6]The structural change literature suggests that sector-specific differential growth in TFP is a source of labor

multiple skill types to perform the same task is also the distinctive feature of the model compared to the existing models of SBTC. While the model successfully rationalizes the monotonic occupation growth patterns, a simple predictive exercise on major occupation groups suggests that predictions of employment share change and wage growth by skill intensity differences across occupations are also compatible with polarization by wages.

I suggest that a labor market view where technical change favors not only high-skill workers but also the occupations employing better skilled ones is an acceptable characterization of the reality. This perspective is also partially compatible with non-monotonic evolution of employment demand along occupational wages. I put forward an additional modification to the task approach by stressing the importance of within-occupation heterogeneity of skills for the dynamics of inequality.

This paper is located within the broad SBTC literature that aims to characterize labor market inequalities in terms of skills. The approach held here can be seen as a combination of the canonical SBTC model with the task-based models. I extend the canonical model to include occupations. On the other hand, this paper diverges from the existing task-based SBTC literature by relaxing the strict assignment of skills to tasks conditional on the state of technology.[7] SBTC at occupation level introduces an alternative channel of task demand shift. Therefore this paper complements the literature on task level sources of disaggregate inequality trends such as routine-biased technical change (e.g., Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014), offshoring (e.g., Blinder, 2009; Jensen and Kletzer, 2010; Blinder and Krueger, 2013), institutional changes (e.g., Lemieux, 2008), and structural change (Barány and Siegel, 2017; Duernecker and Herrendorf, 2017).

On the other hand, this paper contrasts with the existing skill-based interpretation of labor market polarization, which argues that the observed polarization patterns imply polarization of skills in the labor market.[8] The results of this study suggest that the existing occupational polarization can at most be interpreted as polarization of the market value of occupation-specific skills in the face of evidence on monotonic occupation growth by skills that are comparable across occupations.

reallocation (e.g., Ngai and Pissarides, 2007). The same idea can also be applied in the context of occupational structural change (e.g., Autor et al., 2008; Goos et al., 2014).

[7] Acemoglu and Autor (2011) develop a model where three skill types are assigned to a continuum of tasks such that the assignment is subject to change following changes in skill-specific technologies. Autor et al. (2006) and Autor and Dorn (2013) assume that college workers can only perform abstract tasks. Non-college workers can move between routine and manual tasks. In both type of models, conditional on the technology parameters, there is a one-to-one mapping from skill types to tasks.

[8] The discussion in this paper is limited to skill-based interpretation of polarization. Papers that directly test the effect of intensification of recent technologies on the demand for different skill types (e.g., Michaels et al., 2014) remain outside the scope of this paper.

Therefore my results indirectly support the use of models on polarization that employ task-specific skills (e.g., Firpo et al., 2011).[9]

The paper is closest to Cerina et al. (2017) outside the task-based literature. Cerina et al. (2017) develop a multisector model with worker heterogeneity in gender, education and sector-specific ability, where the driver of polarization is SBTC as in this paper. The intuition of the mechanism in their model is that increasing skill premium attracts more women from home production into high-skill service sector, and consequently the demand for services that are substitutable to those produced at home, which are mostly located at the bottom of wage distribution, increases. Two papers differ mainly in terms of the basis of production in the economy. While they have a sector-based model, my study solely focuses on employment and skills in occupations and abstracts from sectors.[10]

The rest of the paper is structured as follows. Section 2 introduces the data used in this paper. Section 3 documents the empirical observations. In particular, first I show the evolution of occupational employment and wages throughout the skill distribution followed by analyses for robustness and validity of the observation. Then I discuss the evidence on the distribution of skills along the wage structure and across occupation groups using several alternative skill measures and on the role of college workers in job polarization. Section 4 introduces the theoretical framework that rationalizes the observations made in previous sections. Section 5 concludes the paper.

2 Data

The main unit of analysis throughout this paper is detailed occupations. I classify occupations following Dorn (2009) who develops a consistent and balanced set of occupation codes that allow comparability across 1980, 1990, 2000 Census, and 2005 American Community Survey (ACS). For occupations in 2010 ACS I first transform 2010 *occ* codes to ACS 2005 *occ* equivalents, and then merge according to the crosswalk by Dorn (2009). Excluding farming and fishing occupations, I end up with a balanced panel of 322 occupations. In some parts of the empirical analyses I also employ six broader (major) 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

[9] Barány and Siegel (2017) and Cerina et al. (2017) also develop Roy-type models to explain job polarization in the US. Although these models apply to sectors the idea can be easily adopted to task-specific abilities.

[10] A further difference is in terms of methodology. Cerina et al. (2017) calibrate their model to explore the implications of the model whereas I follow an essentially descriptive approach here.

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 computed as annual wage income divided by annual hours. Real wages are calculated by an adjustment of nominal hourly wages by Personal Consumption Expenditure (PCE) Index. I have two main skill variables generated from Census data, mean years of education and share of college workers. College worker unless stated otherwise is defined by having any level of education above high school. In the calculation of all occupational averages observations are weighted by labor supply weights which are calculated as annual hours times population weights.

I complement the Census-based education measures by employing a set of variables reflecting different aspects of skills. From National Longitudinal Survey of Youth (NLSY) 1979 I get The Armed Forces Qualification Test (AFQT) score, which is widely used as a measure of general innate ability (Heckman et al., 2006). From 1983 to 1992 the survey reports AFQT scores as well as 3 digit 1980 Census occupation codes. After pooling observations in all years and using the crosswalk by David Dorn 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. One indicates how demanding a job is in terms of working time with a measure of "the typical length of workweek". The other provides a proxy for cognitive demands of the job by the variable "analyzing data or information". Last one is a combined measure of hazardous conditions of the job computed as an average of several related variables.[11] I merge the SOC 2010 codes provided by O*NET to the dataset using 2010 ACS's reported SOC codes and 2010 labor supply weights.

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.

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

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 is prepared by 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).

3 Occupational Skills and Trends in Occupation Growth

3.1 U-Shaped or Monotonic?

In the literature almost all of the evidence for 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 college education. Therefore, I simply start reassessing the role of skills in changing labor market trend by comparing occupational employment and wage growth patterns when occupations are ranked by mean wages to rankings based on high-skill worker intensity. Two alternative variables capture the skill intensity. The first one, college worker share, is the ratio of employment of workers with any college education to the occupation's total employment. The second, college graduate share, is the intensity of workers with at least a college degree in occupation's employment. Figure 2 presents the growth pattern of occupation employment and wages based on the three alternative measures of occupational skill. Panel A and Panel B plot the smoothed employment share changes and real hourly wage growth by the skill percentiles in the 1980 US labor market. Small diamonds in the figure correspond to changes by mean wage ranking and confirm the polarization for the US between 1980 and 2010 in both of measures occupation growth. 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 contrasts 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 2 excludes such concerns.

Figure 2 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 2. 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, gender, age group or the choice of occupational classification. 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.

3.2 Choice of Skill Measure

College worker or college graduate share of employment are relevant metrics for skill intensity from the lens of SBTC hypothesis, but there are other direct measures of skill intensity to check the external validity of the observations in Figure 2. Investigating the robustness of the monotonicity observation with other skill measures can also help understanding the contrasting patterns. For instance, a concern on college intensity measures can be 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. Figure 3 addresses this matter by utilizing a continuous education measure, mean years of schooling.

The smoothed employment share change (Panel A) and wage growth (Panel B) provide evidence in favor of the results based on high-skill intensity in the previous figure. Though, the tendency of occupation growth is not strictly increasing according to mean years of schooling. This is not in contrast with SBTC since the hypothesis does not claim an increasing demand for every year of education. Nevertheless, the linear prediction of the smoothed changes, shown by the continuous line surrounded by the 95 percent confidence interval in Figure 3, can successfully represent the pattern as the R^2 in both panels are above 0.90 and the linearity is statistically significant.

The visual evidence provided above is clear and shares a common methodology to similar studies on labor market polarization. However, construction of percentiles and smoothing procedure can potentially exaggerate the difference between results by wage and education rankings. In addition, it is of interest whether skill measures beyond formal schooling also align with monotonic demand shift towards more skill intensive occupations. Therefore, I formally test the hypothesis whether occupation growth in employment and wages fit better to a u-shaped or linear relationship with respect to skill measures with regressions in the spirit of Goos and Manning (2007).

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

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

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

Table 1 and Table 2 report the regression coefficients on several skill measures when the occupation growth measure is employment share change and real wage growth, respectively. Column (1) of both tables confirm the well-known u-shape with a negative and significant coefficient of the mean wage and a positive significant one for the quadratic term. The u-shape for employment share change in Table 1 is not only significant but strong as suggested by rejection of a simple linear relationship due to the insignificance of the linear term alone in column (2).

Columns (3) to (6) of both tables reestablish the significance of a linear positive relationship between employment share changes and initial mean college share of employment or years of schooling, and further suggest rejection of a u-shaped relationship in line with the evidence provided in previous figures.

The evidence presented so far clearly marks the contrast between wages and education variables in interpreting the direction of occupational demand changes. Yet it may not be sufficient to perfectly overturn the skill-based interpretation of polarization due to two reasons. First, there is unobserved heterogeneity in the quality of education, and the quality of workers is directly reflected into average wages. Therefore wages could reflect the true skill intensity of an occupation better than education variables. This concern is addressed in the regressions by introducing the AFQT scores for each occupation. AFQT is designed to measure trainability and widely used as a cognitive skill measure in the literature. 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. According to columns (7) and (8) of both tables employment share change and wage growth are significantly characterized by a linear positive relationship and not u-shaped with respect to cognitive skill intensity.

The second concern on the education measures of Census can be that while they show the obtained education they could mask the 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 ability 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. Similarly, the middle-wage occupations can also look artificially less skill-intensive if they require education/training on the job while low wage jobs do not. This alternative is tested in columns starting with (9) in both tables by three measures developed to quantify the actual *required* skill intensity of jobs. 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 JZ from ONET. The former is indicated as Training (DOT) and the latter as Training (O*NET) in the tables. In all alternative specifications for both employment share and wage growth equations, there is no evidence of a significant u-shaped pattern. On the contrary all variables perform better in the linear framework. A wide range of skill variables suggest that growth of occupations goes hand in hand with skill intensity.

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, deliver a significant 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.

3.3 Growth Patterns by Decade and Demographic Groups

3.3.1 Occupation Growth in Each Decade

SBTC hypothesis predicts a continuously increasing demand for the more educated. If relative demand changes at occupation level also move in a similar way, then I expect to observe the monotonic employment share and wage changes not only in the long-run but also in smaller frames of time. Figure 4 plots the tendency of employment share changes in each decade from 1980 to 2010 by skill percentiles according to the mean college share in 1980. It should be noted that there is a fall in the strength of linearity of the tendency after 2000, which can be seen by comparing smoothed changes with their linear fit at the Panel C of the figure. Also both the coefficient of each skill percentile and the R^2 decrease in each following decade. Nevertheless, the monotonically increasing pattern for employment growth is confirmed for each decade after 1980.[12]

Figure 5 performs the decadal analysis this time for wage growth. As in employment share change figures, the long-run pattern of occupation growth proportional to skills can be validated within each decade. The monotonicity is slightly violated for the lowest decile of distribution in 1980s and 1990s, which is yet far from implying polarization. Also, in 1990s the wage growth of lower skilled percentiles is higher than their growth in 1980s and 2000s. However in 2000s the monotonic wage growth comes back even stronger as the smoothed changes is perfectly indistinguishable from their linear fit. Figures 4 and 5 jointly support the continuity of skill-biased demand growth at occupation level.

[12] Two related papers (Autor et al., 2006, 2008) observe polarization according to both wage and years of education percentiles during 1990s, which contrasts with the evidence provided here. In appendix section A.1 I discuss the issue in detail and provide evidence showing that the contrasting results stem mainly from the choice of occupational classification.

3.3.2 Occupation Growth in Gender Groups

The literature provides plentiful evidence that the aggregate demand for skilled workers increases regardless of gender. Therefore, it could be expected that the monotonic growth pattern also holds within gender groups. On the other hand, recent papers argue that growth trends in the disaggregate sections of the economy has been affected by female workers (e.g., Ngai and Petrongolo, 2017; Cerina et al., 2017). In order to see if the occupation growth with respect to skills differs by gender, Figure 6 plots smoothed changes by college share of employment when the labor market is split by gender. Both employment and wage growth clearly indicate that the monotonic wage and employment changes take place within both gender groups.

The figure provides additional insights regarding the evolution of gender gaps. In Panel A, employment share of occupations at the upper half of skill distribution increases for both genders at the expense of jobs with lower skill intensity. The shift towards higher skilled occupations is sharper in female employment suggesting that female workers are increasingly represented in skill intensive jobs. While wage growth by gender shown in Panel B is in line with the key observation in this study, it is also possible to track the narrowing gender wage gap from the figure. The change in women's occupational wages tend to be above men. At the same time, wage growth in both gender tend to converge towards higher occupational skill intensity. Both panels therefore imply the previously documented slowdown in the narrowing wage gap after 1980s from a different perspective: women are disproportionately allocated into higher skilled jobs where their wage growth is more similar to men.[13] 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.[14]

3.3.3 Occupation Growth in Age Groups

The behavior of age groups is potentially related to the growth patterns of occupation employment and wages for a number of reasons. First, the demographic structure of the US labor market is significantly affected by the baby-boom cycle. Following the initial decline, the post-1980 period witnessed a sharp increase in the relative supply of experience in both high- and low-skilled labor market (Caselli, 2015).

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

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

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.[15] 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 are becoming older. As a result, other occupations might have been growing solely on the shoulders of younger workers flowing out of the routine-intensive jobs. It would be consistent with this argument to observe that the monotonic growth by skills is driven by employment of relatively younger groups.

In order to address age-related concerns on the key observation of the paper, I plot smoothed occupation growth of employment share and wages for three age groups in Figure 7. Panel A shows employment share change by skills. As opposed to the first concern, the upper tail growth is not particularly confined to older age groups. On the contrary, the employment share growth for the young-age group is significantly higher above the 80th percentile. In contrast to the second concern, it does not seem that young workers play a special role in employment share changes as they evolve very similarly throughout most of the skill distribution.[16]

Panel B presents the occupational wage growth by skills with respect to the three age groups. The figure suggests evidence in favor of the experience-biased technical change as the wage growth tends to be higher for older groups. Aggregate pattern observed in wage growth by skills is also not particularly driven by any 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.[17]

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

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

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

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

3.4 Sensitivity to Occupational Classification

All the analysis so far 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*.[18] These two classifications are inclusive of all the existing occupations but are not balanced in the sense that some occupations in later years do not exist. David Dorn's classification, *occ1990dd*, is an improved version of Meyer and Osborne (2005)'s modification on 1990 Census 3-digit occupation codes (*occ1990*) and provides a balanced set of occupations. Nevertheless, it involves merging of more detailed Census occupation codes and this has the potential of affecting the results. Therefore in order to enable comparison, in this subsection I present the graphical analysis regarding different occupation codes suggested by Census.

Figure 8 shows long run smoothed employment share and 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.

Since skill-biased occupation growth is a robust observation it is important to understand the sources of contrast with the polarization observation, which is the aim of the following subsection.

3.5 Occupational Wage 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 1 provides an early insight: occupational wages in 1980 reflect skills well for the upper half of wage distribution, whereas the occupations' pay structure in the lower part is different than what is predicted by their skill intensity. This is important in skill-based interpretation of polarization since occupational wages are treated as a one dimensional index of skills (Goos and Manning, 2007).

In order to formally test this, I present in Table 3 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. In all cases wages correlate well with skill measures for the upper half of wage distribution (Panel

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

B) and show no significant correlation for the lowest paying half of jobs (Panel A). Additional observations can be made from the table. First, the reported coefficients are small and insignificant for the lower half of wage distribution and the R^2s are too small. Second, training variables have a higher coefficient compared to education variables and AFQT in low wage occupations which implies that firm-specific training possibly have some weight in occupational wage determination but the association is imprecisely estimated and much smaller compared to the high wage group.

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 employment demand in low-wage occupations does not imply a trade-off between middle-skill and low-skill workers but something else. 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 (see Barány and Siegel, 2017, for an example with sector-specific skills).

Therefore as an alternative predictor of the wage structure, I turn to the three-task view of routinization hypothesis (Autor et al., 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 dominates 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. Similarly, the combined routinizability measure of Autor and Dorn (2013), RTI, which jointly reflects routine, non-manual, and abstract task intensity should be increasing along the lower and decreasing along the upper half of the wage structure.

In Table 4 I run occupational wage regressions this time on the task characteristics. First three columns show the association of three task aspects in Autor and Dorn (2013) with wages in the upper and lower half of occupational wage structure. Abstract task content and wages are positively related as expected but not 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 significance. Contrary to the stylized view I do not find a declining wage structure with manual task intensity for the low-wage jobs. Column (4) of panel A of the table shows an unexpected negative association of combined routine task intensity measure of Autor and Dorn (2013) with the lower part of wage structure. The stylized three-task view is also incapable of capturing the 1980 wage structure at detailed occupation level.

Another task driven wage structure explanation is provided by compensating wage differentials literature (Rosen, 1974, 1986). In this explanation 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 4 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 cognitive demands of the job. I proxy this aspect by O*NET work activity variable “Analyzing Data or Information”. The last one measures the hazard involved in the performance of a job by a combination of O*NET variables introduced in Section 2. 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 three of the measures correlate well with wages for low wage group. For high wage occupations all continue to have a positive association except hazardous conditions.

Obviously, these simple OLS regressions do not intend to prove that wages are solely determined according to compensating differentials, but just to show that the skill-based interpretation of polarization remains too naive in assuming lowest skills for occupations of lowest wages. One can find more task-specific aspects that accord with occupational wages better than skill measures, or argue that occupational wages reflect occupation-specific innate ability in the spirit of Roy-type models. All of these potential explanations for why occupational wages and general skill intensity do not overlap at the bottom half of distribution are essentially unrelated to the increasing relative demand for college workers.

The main message from the correlations shown here is that in 1980 the wage structure was not strongly determined by the skill intensity. This sheds light on why skill-based interpretation of labor market polarization does not hold. To the extend that skill intensity and task-specific attributes of jobs deviate in the determination of occupational wages, it becomes harder to observe similar patterns in occupational demand growth by wages and by skills.

3.5.1 Distribution of Skills Across Broader Occupation Groups

The three-skill view of polarization on broader occupation groups suggests distinct roles for some of them. According to this perspective, management, professional and technical jobs are the highest skilled and dominate the top wage distribution. These experience the greatest increases in employment demand. The middle-wage jobs involve production, crafts, transportation, mechanics, operators as well as clerical and office workers whose importance in the labor market sharply declines. The lower tail of wage and skill distribution is occupied by service occupations. Autor and Dorn (2013) show that this last group is responsible from the polarization of the employment demand at the lower half of distribution in the US.[19] Here I present evidence using different skill measures to improve the insights from the broken wage-skill association for lower skilled occupations documented above.

Figure 9 shows the smoothed local means of skills by occupational wage percentiles in 1980 for the set of skill variables regarding six major occupation categories. Calculations are weighted by the 1980 employment share reflecting local means according to labor market importance. Two facts stand in contrast with the stylized three-skill view. First, skills in the service occupations are not very much different than many of the middle-wage occupations. For the lowest wage percentiles where service occupations are the most important regarding polarization, they are never the least skill-intensive occupation group. This observation does not depend on the skill aspect. Education, cognitive capacity or training requirement measures all suggest that low-wage service occupations exhibit skills at least as high as middling occupations except clerical/sale occupations. Second, clerical occupations exhibit the highest skills among middling jobs despite the fact that they get the lowest wages after service occupations. According to most skill measures these jobs are quite close to top wage jobs in terms of skill intensity.

3.6 The High-skill Worker and Polarization

An important implication of the skill-based interpretation of labor market polarization is that high-skill workers are seen as negligible in the reallocation of employment towards the low-wage jobs. In the literature this assumption can be as stark as completely ignoring college workers in the growth of low wage and the decline of middle wage jobs (Autor and Dorn, 2013). Here I briefly argue that the evidence suggests the contrary.

[19] For Europe similar observations regarding the role of low wage service occupations are made by Goos and Manning (2007); Goos et al. (2009, 2014).

Figure 10 shows the 1980-2010 employment share growth of major occupations for college and non-college employment share ranked according to their 1980 wages. Each skill type is separately treated. Darker bars show the growth of non-college employment and lighter bars represent growth rates calculated for college worker employment share. The figure suggests that employment in major occupation groups homogeneously polarizes regardless of the skill category. Workers of both skill type reallocate towards the tails of distribution. An analysis of polarization should therefore involve the presence and growth of high skill workers not only for the top paying jobs but everywhere in the labor market.

3.7 Summary of the Empirical Results

I briefly summarize the key findings of empirical section here. First, employment and wage growth of occupations is increasing in the skill intensity while they follow u-shaped pattern by occupational wages. The skill-biased employment and wage growth of occupations is robust to the choice of skill measure and not particularly driven by a specific decade, gender, age group, or occupation classification. Second, the wage structure in 1980, specifically at the lower half, does not reflect the skill structure of occupations. Rather, task-specific working conditions do a better job in lining up with the wage structure. Third, clerical/sales and service occupations tend to have higher skill intensity throughout the wage distribution although they are paid the lowest wages. Fifth, college and non-college workers seem to take their part in the polarization of employment in every major occupation group. The evidence as a whole suggests that the dispersion in the within-occupation heterogeneity of skills provides valuable information regarding the characterization of trends in occupation growth. In terms of modeling, the results suggest skill-biased technical change at occupation level. In order for this to be consistent with the polarization along the mean wage of occupations, one should include both general skills and other dimension of work conditions, amenities or some form of occupation-specific technical change.

4 A Model of SBTC Within Occupations

4.1 The Model

4.1.1 Overview

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 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 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.[20]

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. In sum, the production side of the model is simply an extension of the canonical 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. Therefore what makes 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 does not accord well with the skill structure and more with task characteristics related to the disutility attached to the job such as time requirement of the job.[21] I assume the simplest form of compensating differentials such that workers are homogeneous in preferences and skills, which can be relaxed to have richer dynamics with respect to technology. For instance, one can further assume that workers of each skill type are heterogeneous in terms of their

[20] See Figure A.1 for stability of the occupational skill structure. The figure compares the wage and skill structure in 1980 and 2010. From the figure it is clear that skill intensity is quite stable both in absolute terms and also when compared to the wage structure in 1980 and 2010.

[21] Another alternative to generate a wage structure that does not overlap with skill-intensity is to assume occupation-specific ability distributions as in Roy-type models.

sensitivity to disutility. 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. In the following, I lay out each piece of the model as introduced above. Then I describe the equilibrium of the model followed by a study of the impact of technical change in this analytic framework.

4.1.2 Final Good Production

The aggregate production function at time t is the following:

$$Y_t = \left(\sum_{j}^{J} \gamma_j \left(T_{jt}\right)^{\rho} \right)^{\frac{1}{\rho}}, \tag{2}$$

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.[22]

The representative firm in the final good market takes task prices p_{jt} as given maximizes profits by choosing task inputs optimally according to:

$$\max_{T_{jt}} \{Y_t - \sum_{j=1}^{J} p_{jt} T_{jt}\}. \tag{3}$$

4.1.3 Task Production

The task production function at time t for occupation j is given by:

$$T_{jt} = \left((\beta_j)^{(1-\mu)} \left(A_{Ht} H_{jt}\right)^{\mu} + (1-\beta_j)^{(1-\mu)} \left(A_{Lt} L_{jt}\right)^{\mu} \right)^{\frac{1}{\mu}}, \tag{4}$$

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. $0 \leq \beta \leq 1$ measures occupation- specific skill intensity, and $\mu < 1$. The elasticity of substitution between skilled and unskilled workers that is constant across occupations is given by $\frac{1}{1-\mu}$. 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.

[22] If one assumes a time varying version of γ_j one can also study occupation-specific demand shifters with this model.

The representative firms in each task market maximize profit by choosing skill inputs optimally according to:

$$\max_{H_{jt}, L_{jt}} \{p_{jt}T_{jt} - w_{Hjt}H_{jt} - w_{Ljt}L_{jt}\}. \tag{5}$$

4.1.4 Households

The consumer side is characterized by the following utility function for each worker with skill level S working in occupation j:

$$U_{Sjt} = \log(C_{Sjt}) - \log(d_j), \tag{6}$$

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:

$$C_{Sjt} = w_{Sjt}, \tag{7}$$

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.

4.1.5 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 according to (3), and task producers in each occupation optimally choose high-skill (H_{jt}) and low-skill (L_{jt}) labor input following (5).

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 $\sum_{j=1}^{J} \left(H_{jt}C_{Hjt} + L_{jt}C_{Ljt}\right) = Y_t$

4.2 Occupational Wage and Skill Hierarchy, and Their Stability

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:

$$\frac{w_{Sjt}}{d_j} = \frac{w_{Sj't}}{d_{j'}}. \tag{8}$$

Equation (8) suggests that conditional on skill-type 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.[23] This can be seen by comparing the mean wages in two arbitrary occupations:

$$\frac{w_{jt}}{w_{j't}} = \frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hjt} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Ljt}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} = \left(\frac{d_j}{d_{j'}}\right) \left(\frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hj't} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Lj't}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} \right), \tag{9}$$

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. From equation (9) 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 (9) also suggests that relative wages are affected by the increase in high-skill

[23] 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 μ.

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.

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:

$$\frac{\beta_j}{\beta_{j\prime}} \frac{1-\beta_{j\prime}}{1-\beta_j} = \frac{H_j}{H_{j'}} \frac{L_{j'}}{L_j}. \tag{10}$$

Equation (10) 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 βs 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.1. 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.

4.3 The College Wage Premium

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 skill premium equation can be expressed as follows:

$$\log\left(\frac{w_{Ht}}{w_{Lt}}\right) = \log\left(\frac{\beta_1}{1-\beta_1}\right) + \mu \log\left(\frac{A_{Ht}}{A_{Lt}}\right) + (\mu-1)\log\left(\frac{H_t}{L_t}\right) + \Gamma_{HLt}, \tag{11}$$

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 the premium equation of the canonical model in terms of the two forces that is expressed as the race between education by Tinbergen (1974), namely the relative growth of skill-specific technology (relative skill demand) and of relative skill supply. The evolution of skill premium differs from the canonical model because of the last term on the right hand side. It captures that in the occupation augmented SBTC model there are two additional potential sources which can affect the aggregate skill premium. First is the changes in the ratio of high skill 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 (11) is identical to canonical SBTC model if skill intensity parameter β and disutility parameter d are identical across occupations.

4.4 Technical Change and the Evolution of Occupational Demand

In this part of the section I study the implications of the model on occupational wage growth and reallocation of labor. Since the model is static, the results are based on assumptions on the direction of the technical change following the literature. Skill-biased technical change when combined with the model's key feature of skill heterogeneity within occupations, appears as a fundamental driver of the occupational reallocation of labor. The simple reason is that substantial bias of demand growth towards high-skill workers may also increase 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 results on changes in occupational labor demand, which brings together the key empirical observations of the previous section.

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 β_j and do not depend on the wage structure. There exists a combination of disutility parameters d_j and skill intensity parameters β_j so that employment share changes and mean wage growth implies polarization, i.e., higher growth of employment and mean wage at the tails of wage structure relative to middle.*

I provide the formal proof in 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. Note that in these results the key parameter is skill intensity, hence these results hold under any wage structure.[24]

The model does not strictly imply polarization. However, it is possible to observe polarization-like patterns along occupational mean wages if the least skill intensive occupations are positioned in the middle of wage distribution. As discussed in the previous part, 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. This result is only a matter of how occupational wages are ordered, but if the ordering is suitable the driving force of the observed polarization is skill-biased occupational demand change of the model. Therefore, the model is capable of combining the key observation made in the section 3, that is monotonic growth by occupational skills simultaneously with polarization along occupational wages.

4.4.1 Alternative Drivers of Occupation Growth

The proposition suggests the 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, clearly there are other sources within the model's framework that 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

[24] 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.

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 (equation (10)). 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 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 (11)) as $\mu < 1$.

Second, although introduced as fixed in the model the skill intensity parameter β_j can be subject to change. In this case, an additional impact comes from the alteration of the skill structure. In this case, 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 Figure A.1) suggests that this potential driver of occupation growth is very likely to have limited impact.

Figure A.2 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 β_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 the ranking of occupations, which is close to the tendency of actual changes in skill intensity shown in the figure.

4.5 Predicting Labor Market Polarization by Skill Intensity

It is beyond the aim of this paper to quantify the impact of occupation-based SBTC in actual polarization, however suggestive evidence is presented here to complement the discussion. In order to illustrate how much the extended SBTC view introduced above can help to understand labor market polarization in addition to monotonic demand shifts, I perform a simple prediction with the data used in Section 3. I predict the employment share change and mean wage growth of major occupation groups between 1980 and 2010 using 1980 skill intensity of occupation groups.

Figure 11 shows the skill intensity-predicted and actual employment share changes in the upper panel, and mean wage growth in the lower panel, by 1980 mean wage of occupation groups on the horizontal axis. The dashed lines with rectangles represent actual changes of the corresponding variable. The solid lines with circles show the predicted change in employment share or mean log real wage. Employment and wage polarization are manifested by greatest increases in the high-wage management, professional, and finance as well as lowest paid clerical, and personal services occupations at the expense of middling occupation groups in both parts of the figure. A remarkably similar pattern is shown by the skill intensity predictions. Using occupation level measures of skills is promising in generating the non-monotonic trends observed in the labor market.

While predicted employment share and log wage changes are quite close to actual in general and exhibit the employment polarization pattern, the details in the figure provide additional insights. First, the predicted employment share change is a little higher than the actual for clerical and retail sales occupation group and lower for personal services occupations, which suggests that the rise of personal services can only be partially explained by skill-biased technical change. On the other hand, skill intensity can successfully capture the relatively higher growth of wages in clerical occupations, which is found as puzzling in routinization literature (Autor and Dorn, 2013).

5 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 labor market polarization observed along occupational wage distribution after 1980 disappears when the skill measure is changed to other and more direct measures of occupational skill intensity 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 almost monotonically, 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. If the level of wages are determined by occupation-specific factors rather than general skills, the model can also help understanding part of polarization phenomena. This does not rule out 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 occupational quality ladder. The findings presented here suggest 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. My 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 determinants of observable skill intensity differences across occupations.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4:1043–1171.

Acemoglu, D. and Autor, D. (2012). What does human capital do? A review of Goldin and Katz's The race between education and technology. *Journal of Economic Literature*, 50(2):426–463.

Autor, D. and Dorn, D. (2009). This Job is "getting old": Measuring changes in job opportunities using occupational age structure. Technical report.

Autor, D. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *The American Economic Review*, 103(5):1553–1597.

Autor, D., Katz, L. F., KEARNEY, M. S., David, H., Katz, L. F., and KEARNEY, M. S. (2006). The polarization of the US labor market. *The American economic review*, 96(2):189–194.

Autor, D., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4).

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in US wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2):300–323.

Barány, Z. and Siegel, C. (2017). Job polarization and structural change. *American Economic Journal: Macroeconomics, forthcoming.*

Blau, F. D. and Kahn, L. M. (2006). The US gender pay gap in the 1990s: Slowing convergence. *Industrial & Labor Relations Review*, 60(1):45–66.

Blinder, A. S. (2009). How many US jobs might be offshorable? *World Economics*, 10(2):41.

Blinder, A. S. and Krueger, A. B. (2013). Alternative Measures of Offshorability: A Survey Approach. *Journal of Labor Economics*, 31(2 Part 2):S97—-S128.

Bryson, A., Barth, E., and Dale-Olsen, H. (2012). Do higher wages come at a price? *Journal of Economic Psychology*, 33(1):251–263.

Bryson, A. and MacKerron, G. (2016). Are you happy while you work? *The Economic Journal.*

Caselli, F. (2015). Experience-biased Technical Change. *CFM Discussion Paper 1517*, (August 2014).

Cerina, F., Moro, A., and Rendall, M. (2017). The role of gender in employment polarization. Technical report, University of Zurich, Department of Economics.

Dorn, D. (2009). *Essays on inequality, spatial interaction, and the demand for skills*. PhD thesis, University of St. Gallen.

Duernecker, G. and Herrendorf, B. (2017). Structural transformation of occupation employment.

England, P. and Kilbourne, B. (1988). Occupational Measures from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations.

Firpo, S., Fortin, N. M., and Lemieux, T. (2011). Occupational tasks and changes in the wage structure. *IZA Discussion Paper*.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *The American Economic Review*, 104(4):1091–1119.

Goldin, C., Katz, L. F., and Kuziemko, I. (2006). The homecoming of American college women: The reversal of the college gender gap. *The Journal of Economic Perspectives*, 20(4):133.

Goldin, C. D. and Katz, L. F. (2008). *The Race Between Education and Technology*. Harvard University Press.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. *The American Economic Review*, 99(2):58–63.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *The American Economic Review*, 104(8):2509–2526.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, 24(3):411–482.

Jensen, J. B. and Kletzer, L. G. (2010). Measuring tradable services and the task content of offshorable services jobs. *Labor in the New Economy*, (October):309–335.

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Lemieux, T. (2008). The changing nature of wage inequality. *Journal of Population Economics*, 21(1):21–48.

Meyer, P. B. and Osborne, A. M. (2005). Proposed category system for 1960-2000 census occupations.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, 96(1):60–77.

Ngai, L. R. and Pissarides, C. A. (2007). Structural change in a multisector model of growth. *The American Economic Review*, 97(1):429–443.

Ngai, R. and Petrongolo, B. (2017). Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics (Forthcoming)*.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1):34–55.

Rosen, S. (1986). The theory of equalizing differences. *Handbook of labor economics*, 1:641–692.

Tinbergen, J. (1974). Substitution of graduate by other labour. *Kyklos*, 27(2):217–226.

Tables

Table 1: Employment Share Change and Skills

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Wage	-8.05***	0.10												
	(2.87)	(0.28)												
Wage Squared	1.54***													
	(0.55)													
College Share			0.28	0.92***										
			(1.41)	(0.21)										
College Share Squared			0.65											
			(1.40)											
Years of Sch.					-0.11	0.12***								
					(0.51)	(0.03)								
Years of Sch. Squared					0.01									
					(0.02)									
AFQT							-0.23	0.13***						
							(0.34)	(0.04)						
AFQT Squared							0.04							
							(0.03)							
GED									-0.51	0.21***				
									(0.60)	(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)													0.22**	0.11***
													(0.10)	(0.03)
Training (O*NET) Squared													-0.02	
													(0.01)	
Constant	10.20***	-0.46	-0.44*	-0.54***	-0.23	-1.70***	0.03	-0.84***	0.35	-0.96***	-0.27*	-0.32**	-0.52***	-0.40***
	(3.71)	(0.80)	(0.23)	(0.15)	(3.33)	(0.42)	(0.82)	(0.24)	(1.09)	(0.26)	(0.16)	(0.14)	(0.18)	(0.14)
Observations	322	322	322	322	322	322	321	321	322	322	322	322	322	322
R^2	0.06	0.00	0.13	0.12	0.10	0.10	0.08	0.07	0.08	0.06	0.03	0.02	0.09	0.08

Notes: Each column 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 text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Wage Growth and Skills

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Wage	-1.49***	0.09*												
	(0.55)	(0.05)												
Wage Squared	0.30***													
	(0.11)													
College Share			1.00***	0.38***										
			(0.18)	(0.06)										
College Share Squared			-0.63***											
			(0.21)											
Years of Sch.					0.27***	0.05***								
					(0.10)	(0.01)								
Years of Sch. Squared					-0.01**									
					(0.00)									
AFQT							0.06	0.07***						
							(0.05)	(0.01)						
AFQT Squared							0.00							
							(0.01)							
GED									0.02	0.11***				
									(0.11)	(0.02)				
GED Squared									0.01					
									(0.02)					
Training (DOT)											0.03	0.03***		
											(0.03)	(0.01)		
Training (DOT) Squared											0.00			
											(0.00)			
Training (O*NET)													0.11***	0.05***
													(0.02)	(0.01)
Training (O*NET) Squared													-0.01***	
													(0.00)	
Constant	1.99***	-0.07	-0.09***	0.01	-1.89***	-0.49***	-0.17	-0.21***	-0.09	-0.26***	0.09**	0.09***	0.00	0.06***
	(0.69)	(0.13)	(0.03)	(0.02)	(0.65)	(0.11)	(0.13)	(0.04)	(0.20)	(0.06)	(0.04)	(0.03)	(0.03)	(0.02)
Observations	322	322	322	322	322	322	321	321	322	322	322	322	322	322
R^2	0.06	0.02	0.43	0.37	0.37	0.33	0.38	0.38	0.32	0.32	0.14	0.14	0.38	0.32

Notes: Each column shows 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 text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Predicting Occupational Skills with Wages

(Dependent Variable: Percentile Ranking of Occupational Skill Measures)

	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (O*NET)
A. Lower Half of 1980 Wage Distribution						
Wage Percentile Rank	-0.02	0.04	-0.05	0.14	0.38	0.18
	(0.19)	(0.20)	(0.17)	(0.22)	(0.25)	(0.17)
Constant	0.36***	0.34***	0.38***	0.30***	0.18***	0.29***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
Observations	161	161	160	161	161	161
R^2	0.00	0.00	0.00	0.01	0.08	0.01
B. Upper Half of 1980 Wage Distribution						
	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (O*NET)
Wage Percentile Rank	0.65***	0.68***	0.67***	0.59***	0.86***	0.58***
	(0.21)	(0.19)	(0.17)	(0.15)	(0.14)	(0.18)
Constant	0.16	0.14	0.14	0.23*	0.01	0.25*
	(0.17)	(0.16)	(0.14)	(0.12)	(0.11)	(0.14)
Observations	161	161	161	161	161	161
R^2	0.11	0.13	0.14	0.14	0.22	0.12

Notes: 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 text for skill variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Predicting Occupational Skills with Tasks

(Dependent Variable: Percentile Ranking of Occupational Task Measures)

	Abstract	Manual	Routine	RTI	Time Demand	Cognitive Demand	Hazard
A. Lower Half of 1980 Wage Distribution							
Wage Percentile Rank	0.15	0.48	0.12	-0.46***	0.90***	0.57***	0.67***
	(0.25)	(0.34)	(0.15)	(0.34)	(0.17)	(0.16)	(0.18)
Constant	0.31***	0.36***	0.50***	0.70***	0.10***	0.23***	0.29***
	(0.05)	(0.10)	(0.10)	(0.04)	(0.04)	(0.05)	(0.06)
Observations	161	161	161	161	161	161	161
R^2	0.01	0.05	0.00	0.05	0.35	0.15	0.13
B. Upper Half of 1980 Wage Distribution							
	Abstract	Manual	Routine	RTI	Time Demand	Cognitive Demand	Hazard
Wage Percentile Rank	0.86***	-0.27	-0.56*	-0.53***	0.70***	0.84***	-0.56***
	(0.15)	(0.23)	(0.29)	(0.17)	(0.16)	(0.21)	(0.19)
Constant	0.07	0.68***	0.83***	0.77***	0.21*	0.02	0.90***
	(0.11)	(0.18)	(0.22)	(0.13)	(0.11)	(0.15)	(0.15)
Observations	161	161	161	161	161	161	161
R^2	0.24	0.02	0.05	0.05	0.19	0.18	0.06

Notes: 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 text for task variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figures

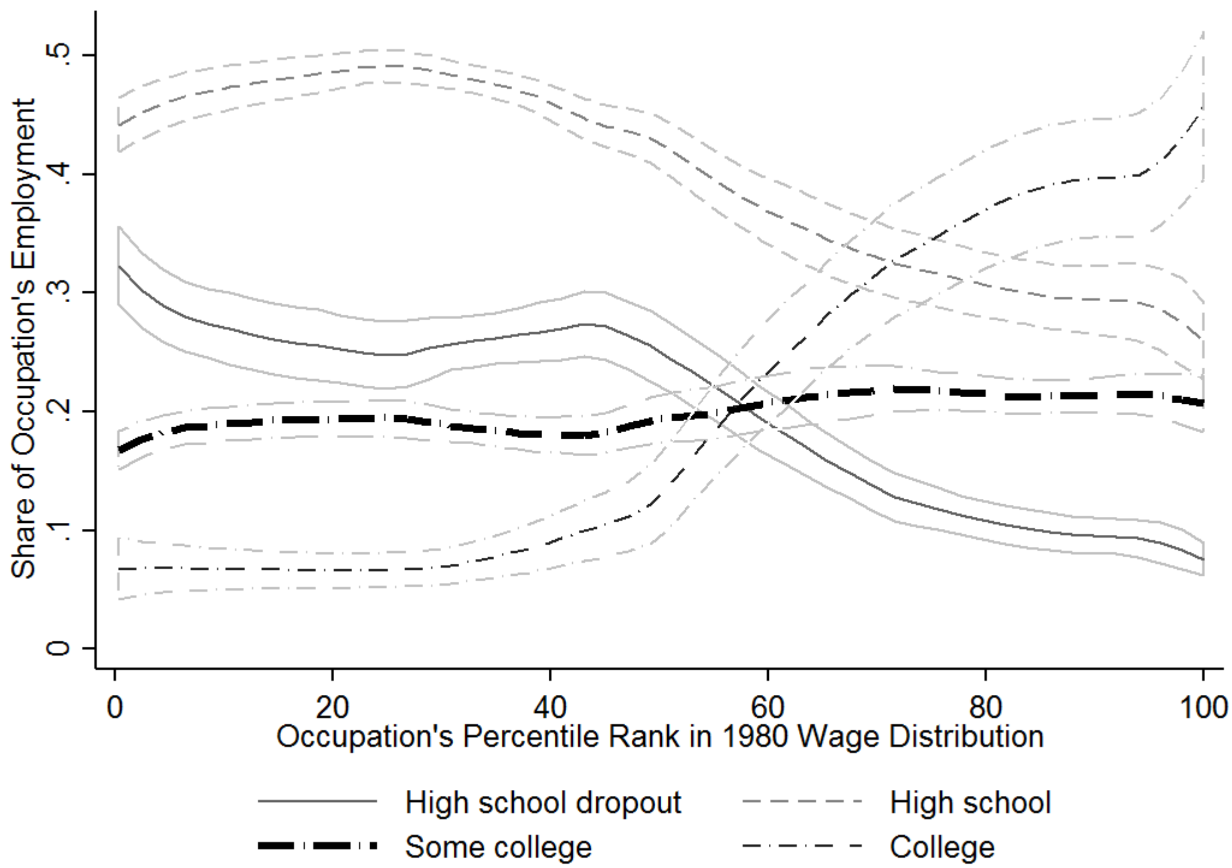


Figure 1: Occupational Skill Intensity and Wage Structure

Notes: 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 322 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.

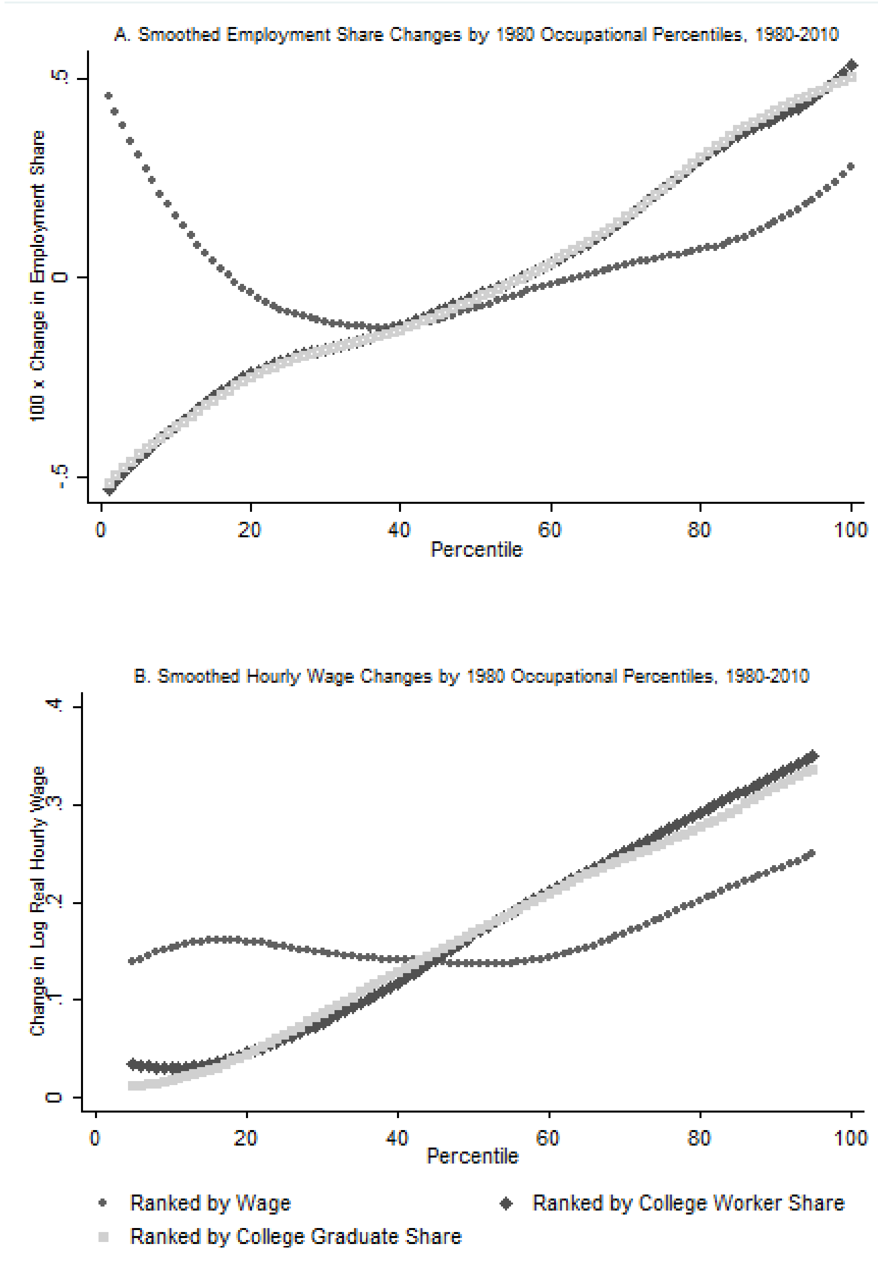


Figure 2: Change in Occupational Employment Share and Log Real Wages by Wage and Skill Percentiles

Notes: 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 322 consistent non-farm occupations following Dorn (2009)'s classification. Construction of employment percentiles, computation of mean wages in each percentile and smoothing procedure follows 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.

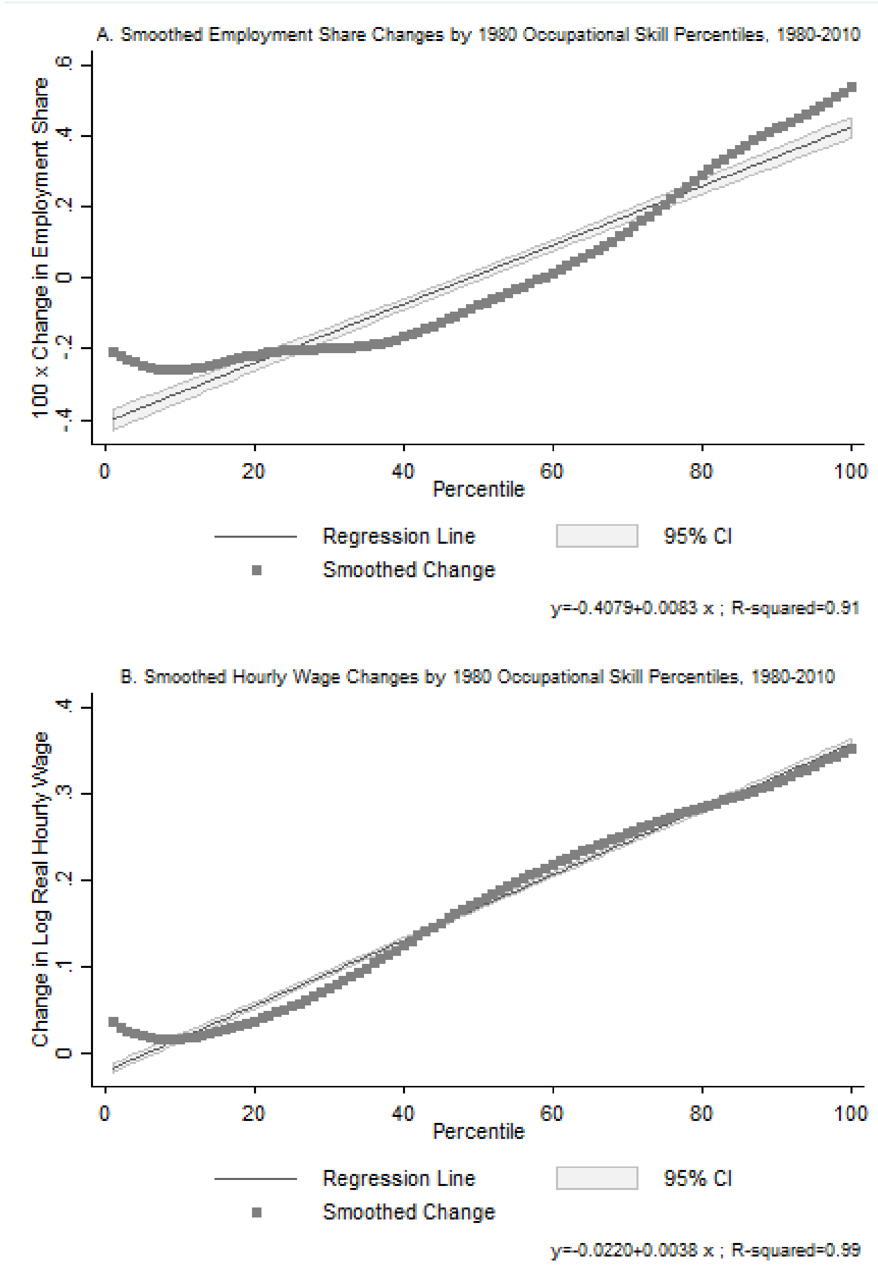


Figure 3: Occupational Employment Share Change and Real Wage Growth by Mean Years of Education

Notes: The figure shows smoothed 1980-2010 changes in occupational employment share and log real wages of occupations ranked by 1980 occupational mean years of education. The gray colored squares 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. For all other details see Figure 2 notes.

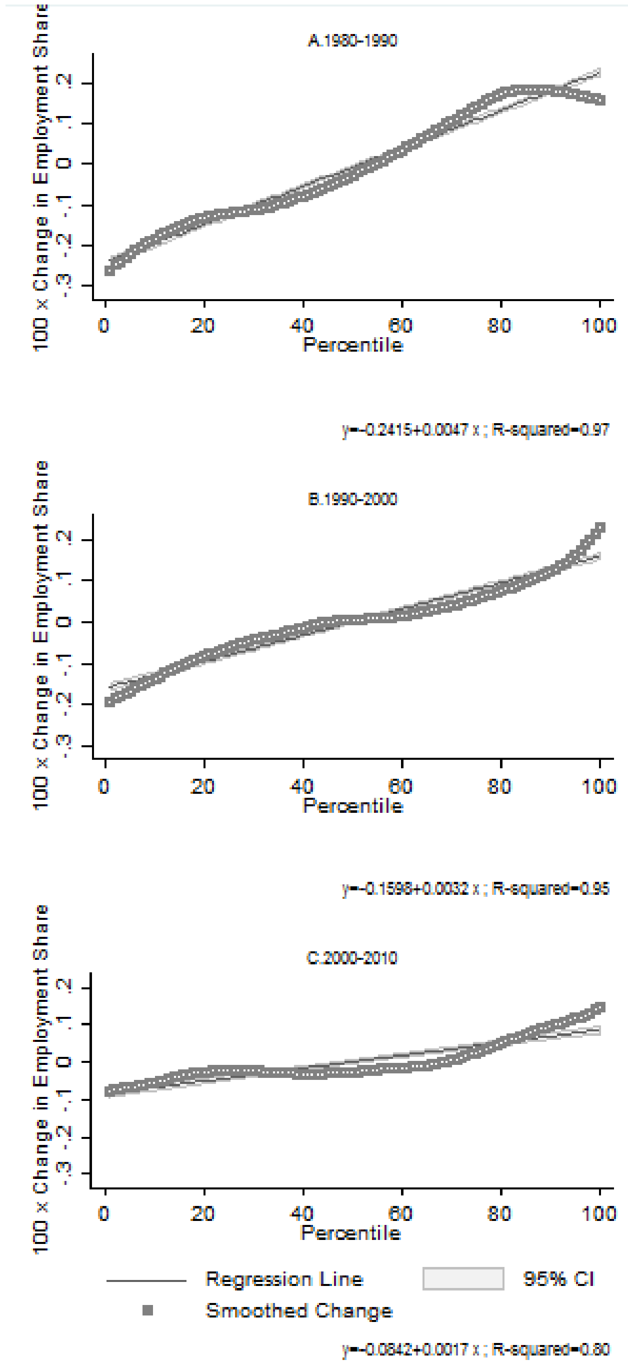


Figure 4: Decadal Changes in Occupational Employment Share by Skill

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. The gray colored squares 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. For all other details see Figure 2 notes.

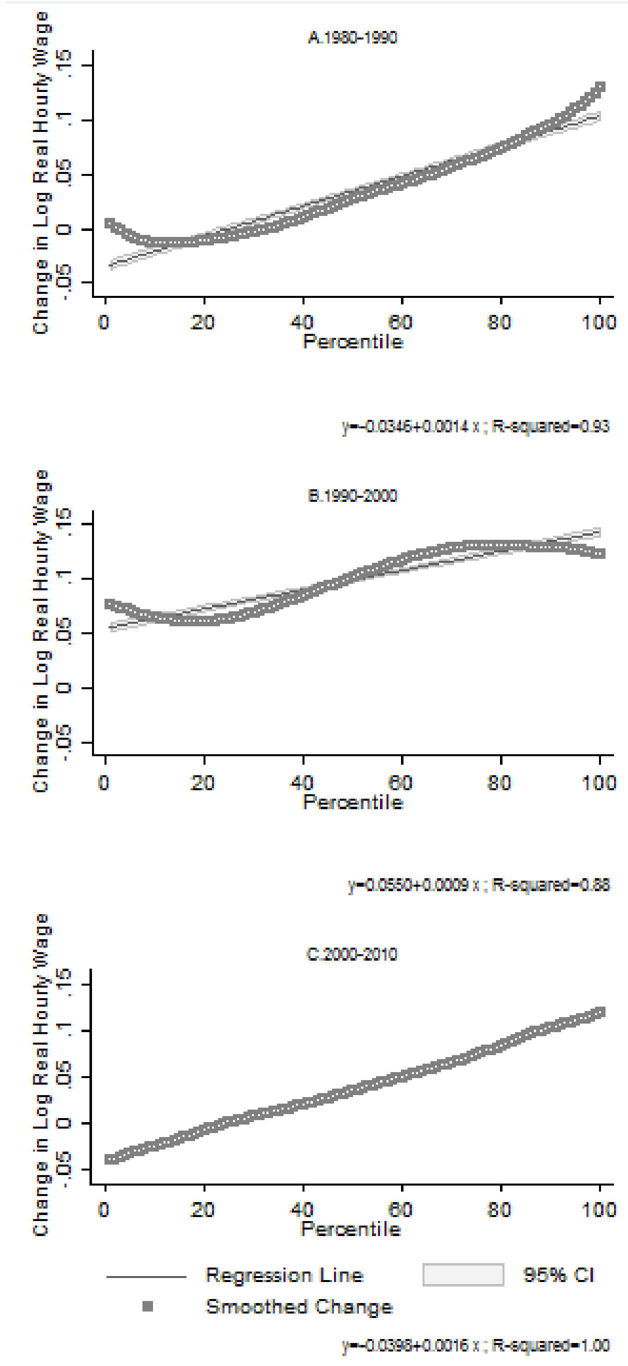


Figure 5: Decadal Changes in Occupational Real Wage by Skill

Notes: The figure shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in occupational mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment. The gray colored squares 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. For all other details see Figure 2 notes.

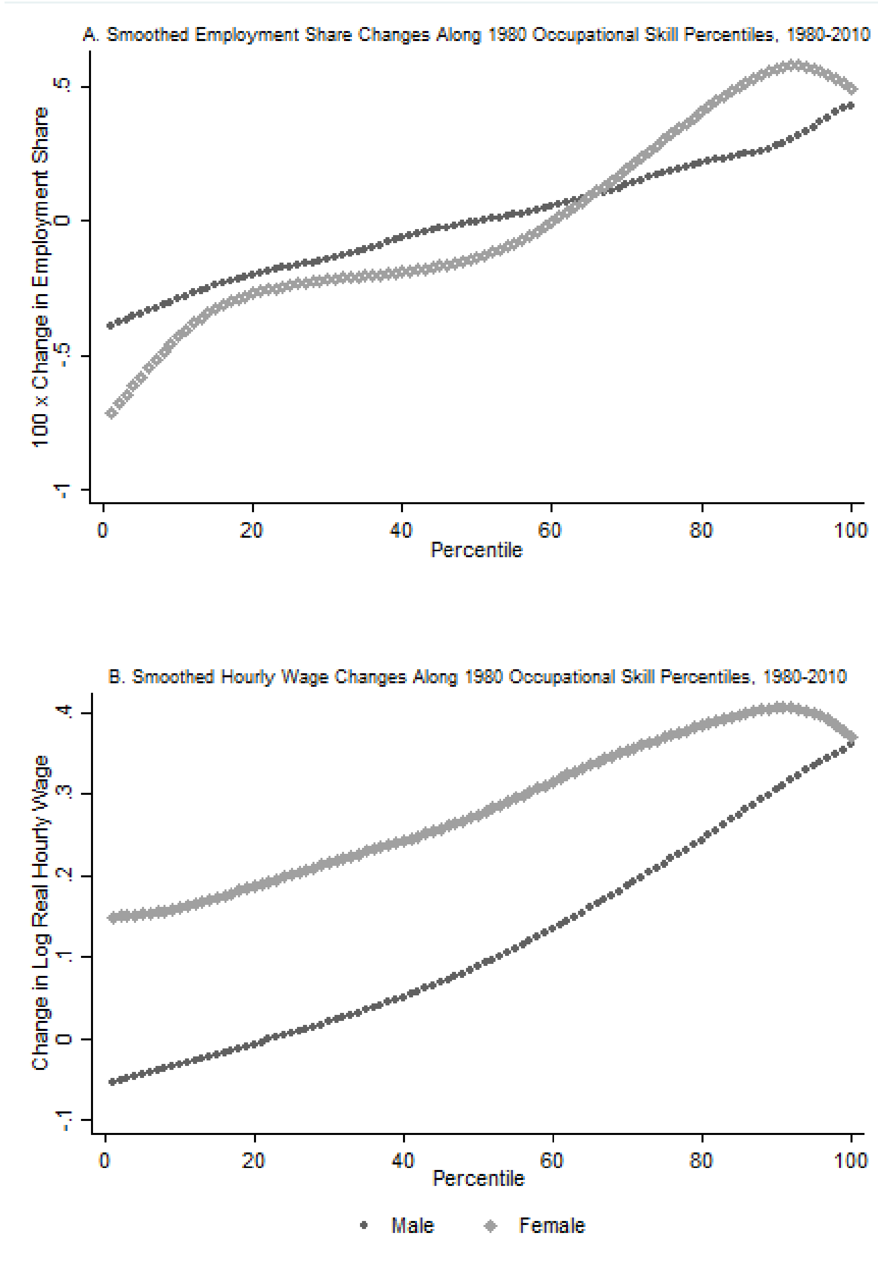


Figure 6: Monotonic Occupation Growth by Gender

Notes: 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. For all other details see Figure 2 notes.

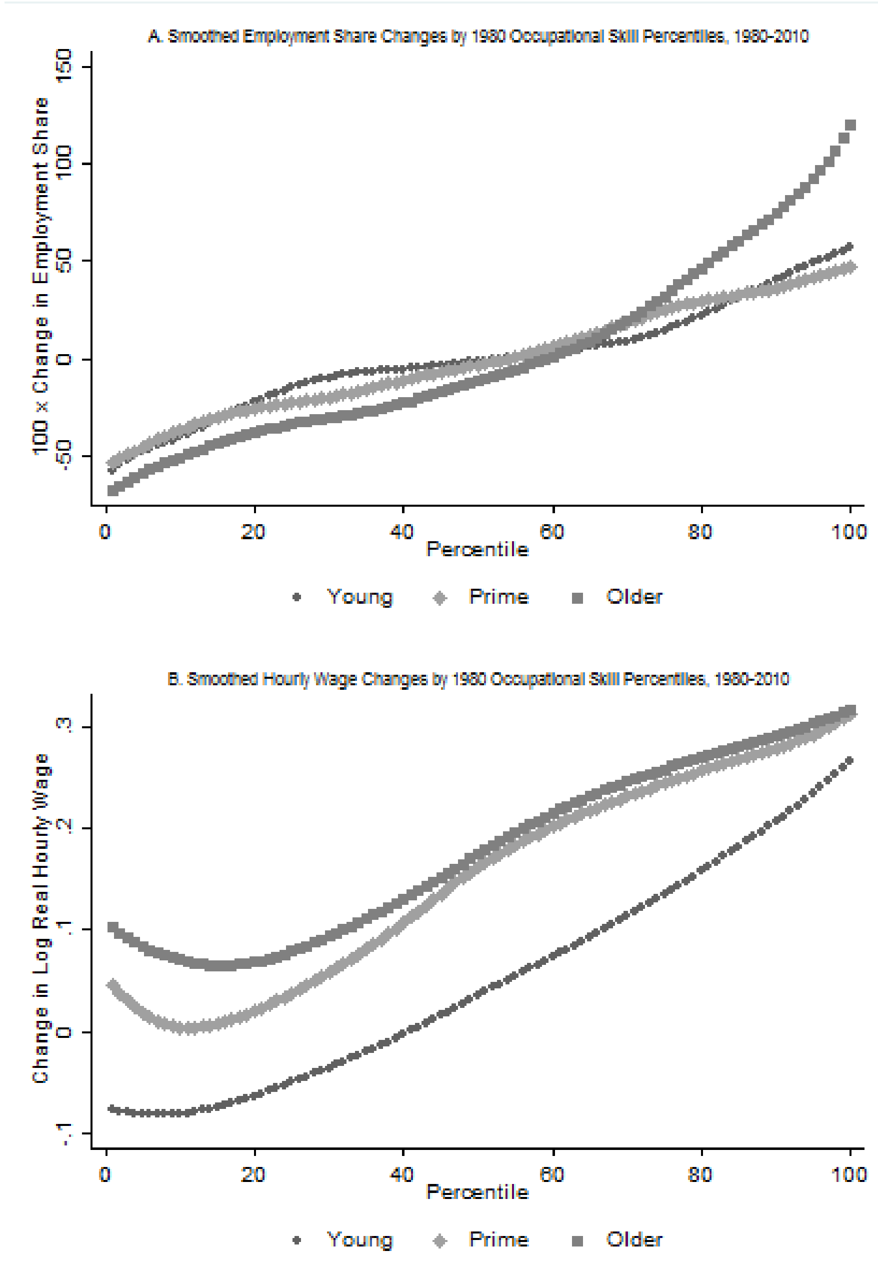


Figure 7: Monotonic Occupation Growth by Age

Notes: 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. For all other details see Figure 2 notes.

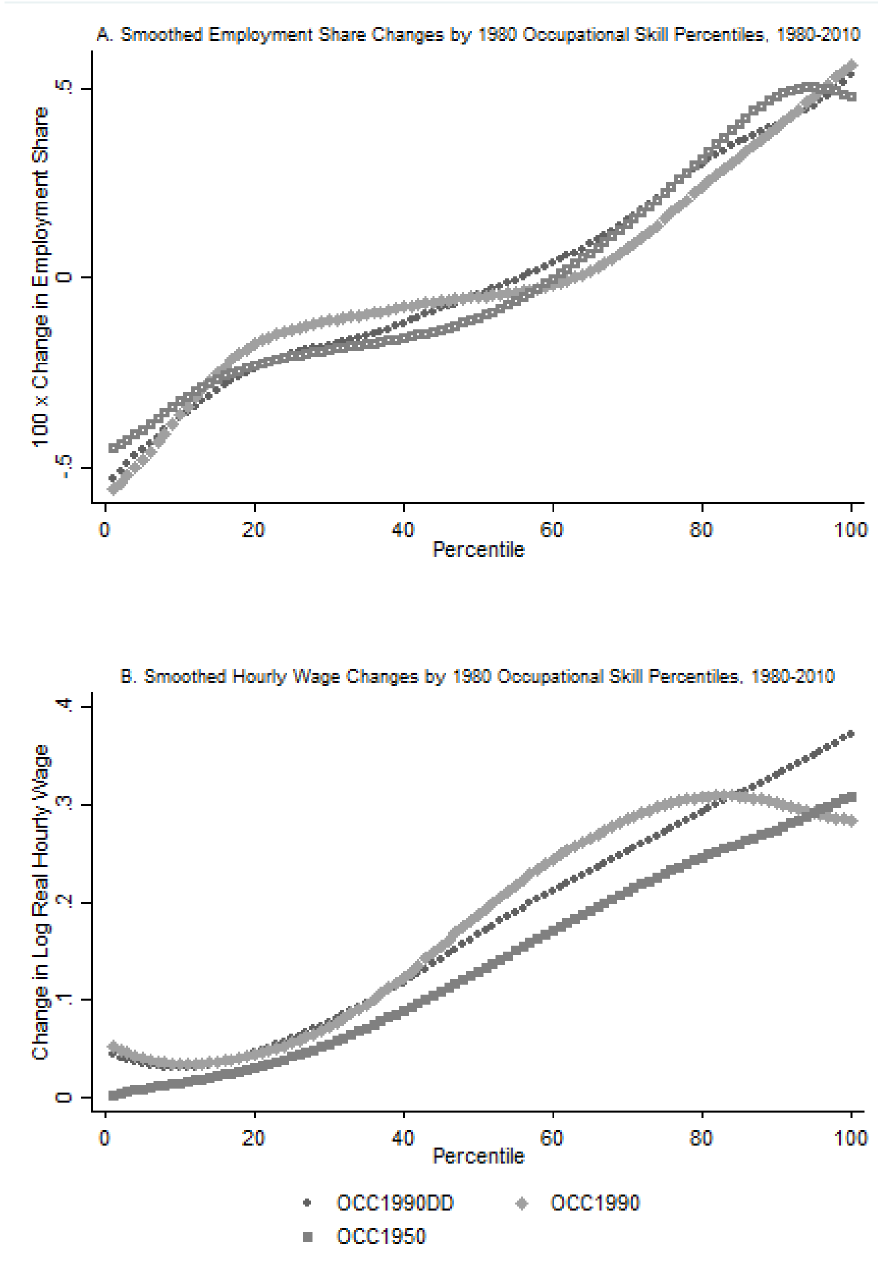


Figure 8: Monotonic Occupation Growth and Occupation Classification

Notes: 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.

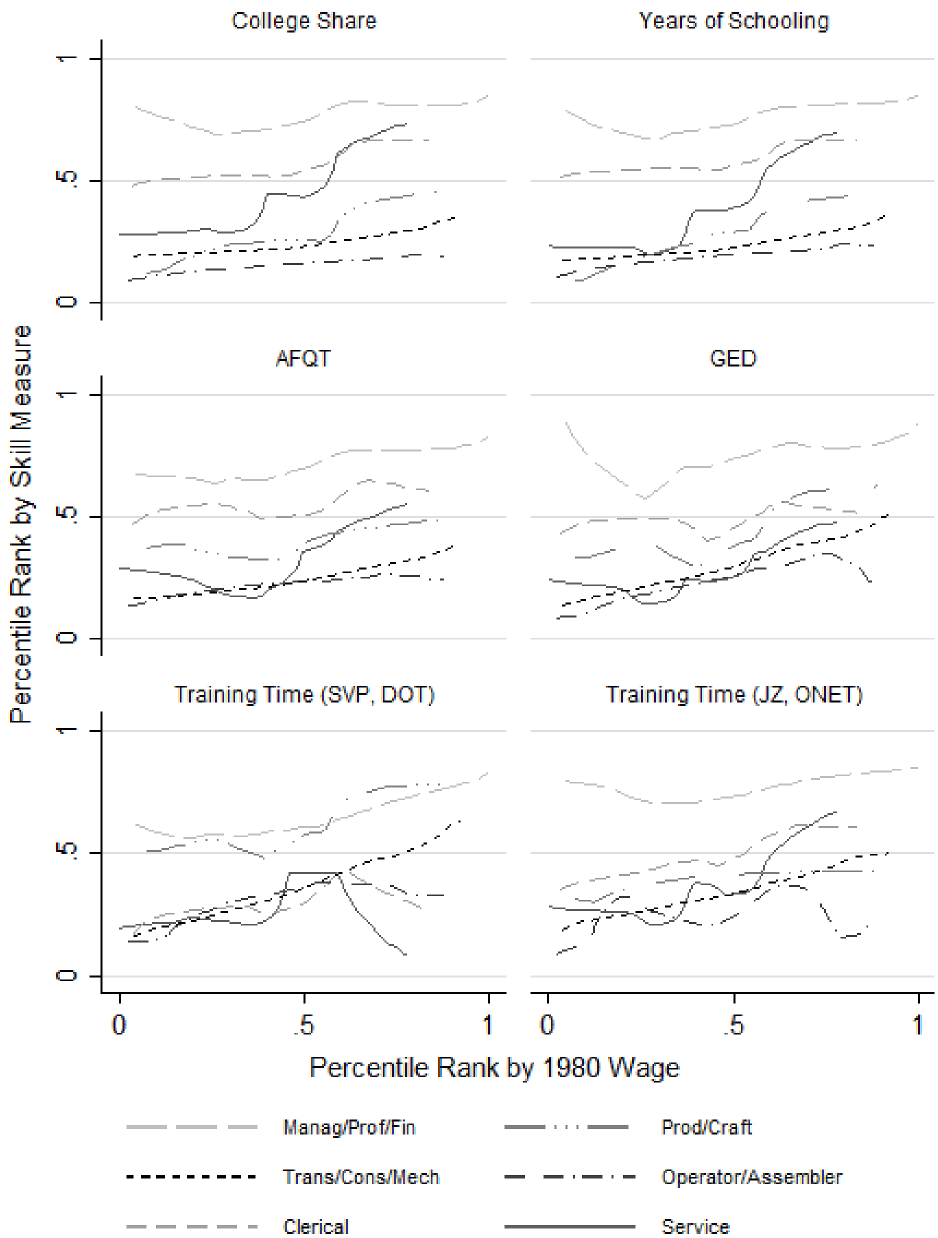


Figure 9: Skills and Wages by Occupation Group

Notes: The figure shows smoothed 1980 occupational mean skill intensity measures by occupations' 1980 mean wage percentile ranks (from 0 to 1) for major occupation groups. Smoothing is performed by local polynomials and weighted by occupations' employment shares. See text for details on skill variables.

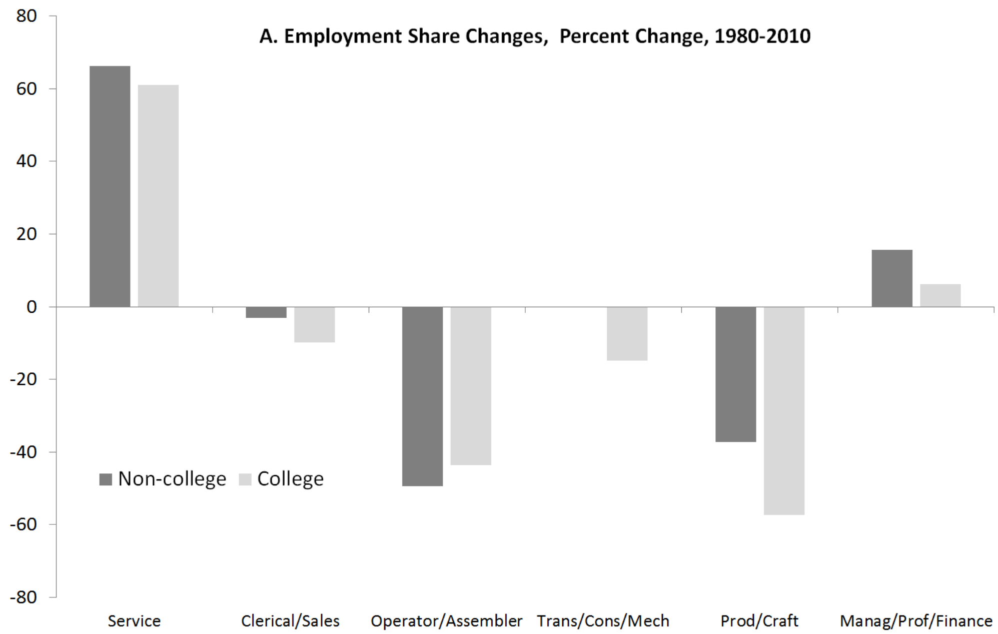
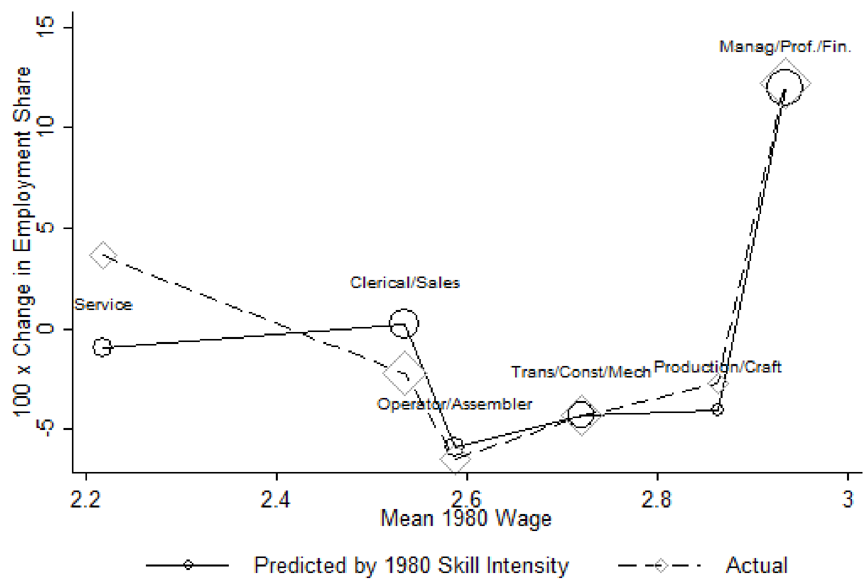


Figure 10: Polarization of College and Non-college Employment

Notes: The figure shows percentage change in employment share of major occupation groups separately by college and non-college workers. Occupation groups are ordered from left to right according to 1980 mean wages.



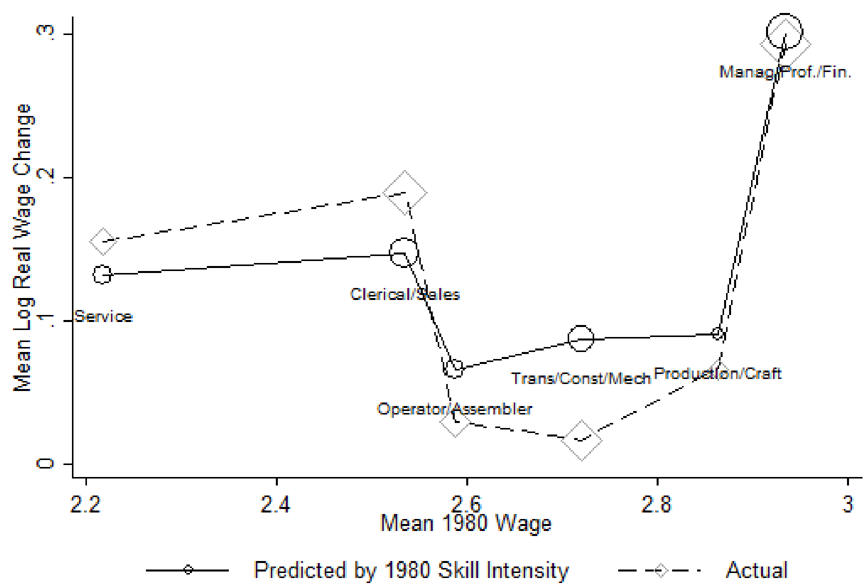


Figure 11: Actual and Predicted Employment Share Change and Wage Growth, 1980-2010

Notes: The figure shows actual and predicted employment share and mean log real wage changes by major occupations. Predicted changes are obtained by regressing the actual changes on the occupation group's skill intensity proxied by the college worker share of the median occupation in that group.

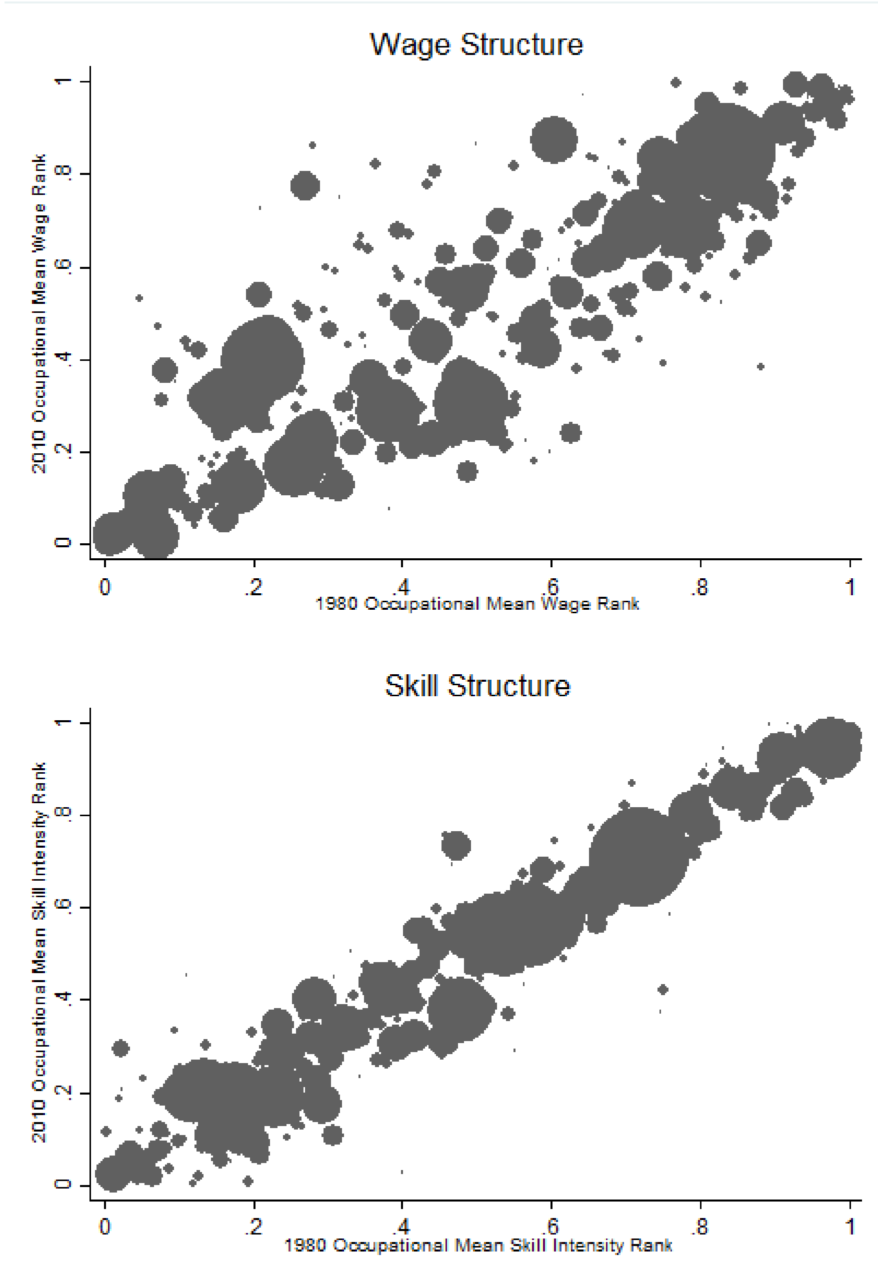


Figure A.1: Wage and Skill Structure in the Long Run, 1980-2010

Notes: 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.

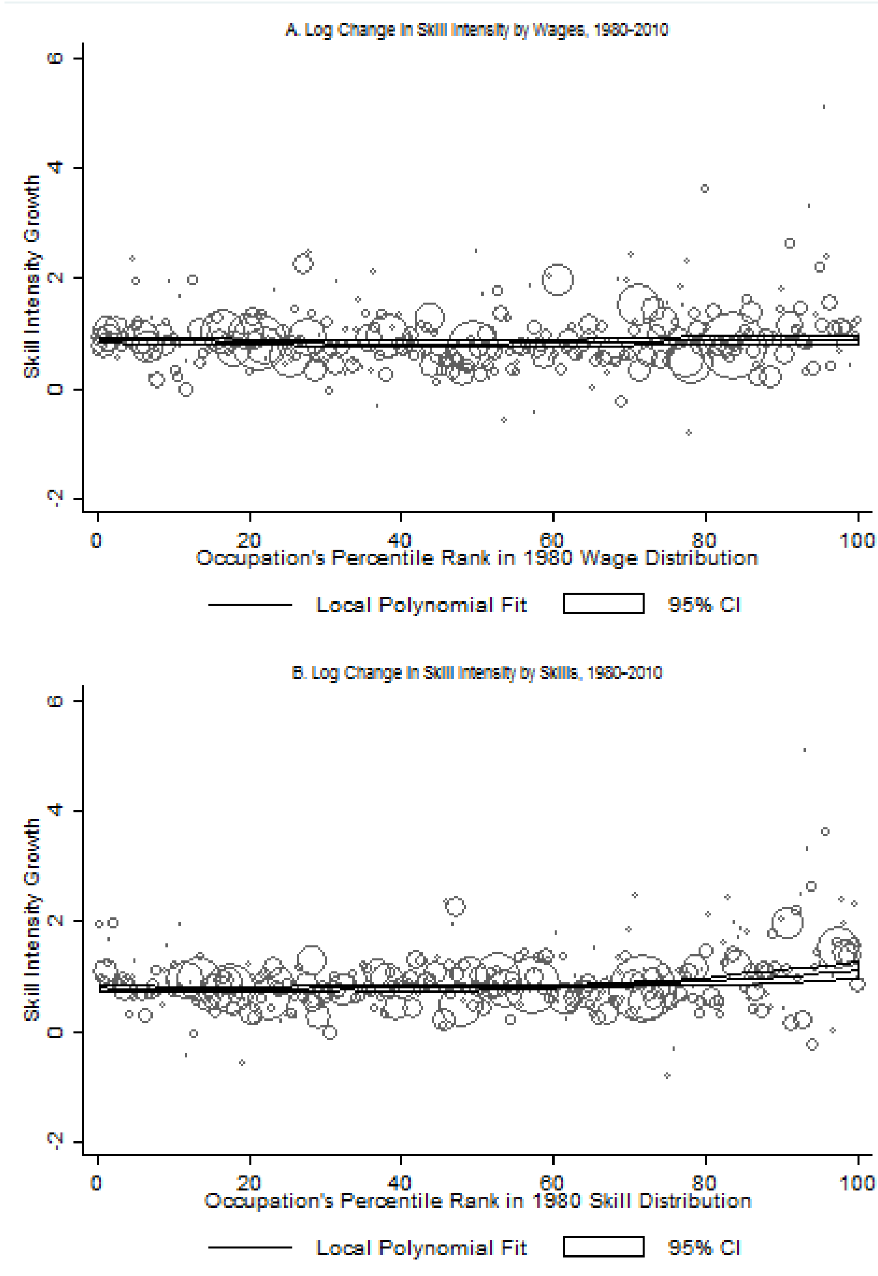


Figure A.2: Change in Skill Intensity, 1980-2010

Notes: 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.

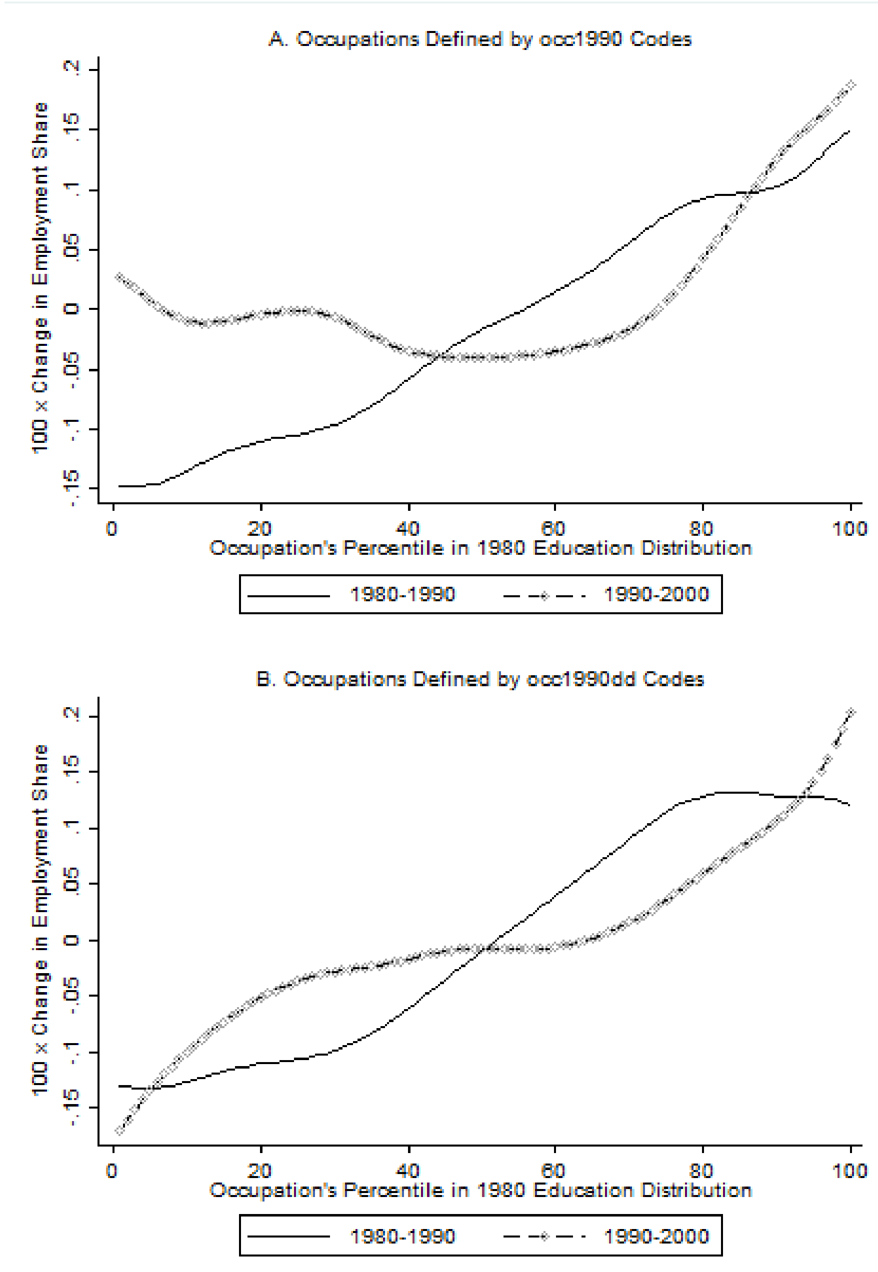


Figure A.3: Smoothed Changes in Employment Share by Skill Percentile and Occupation Codes

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

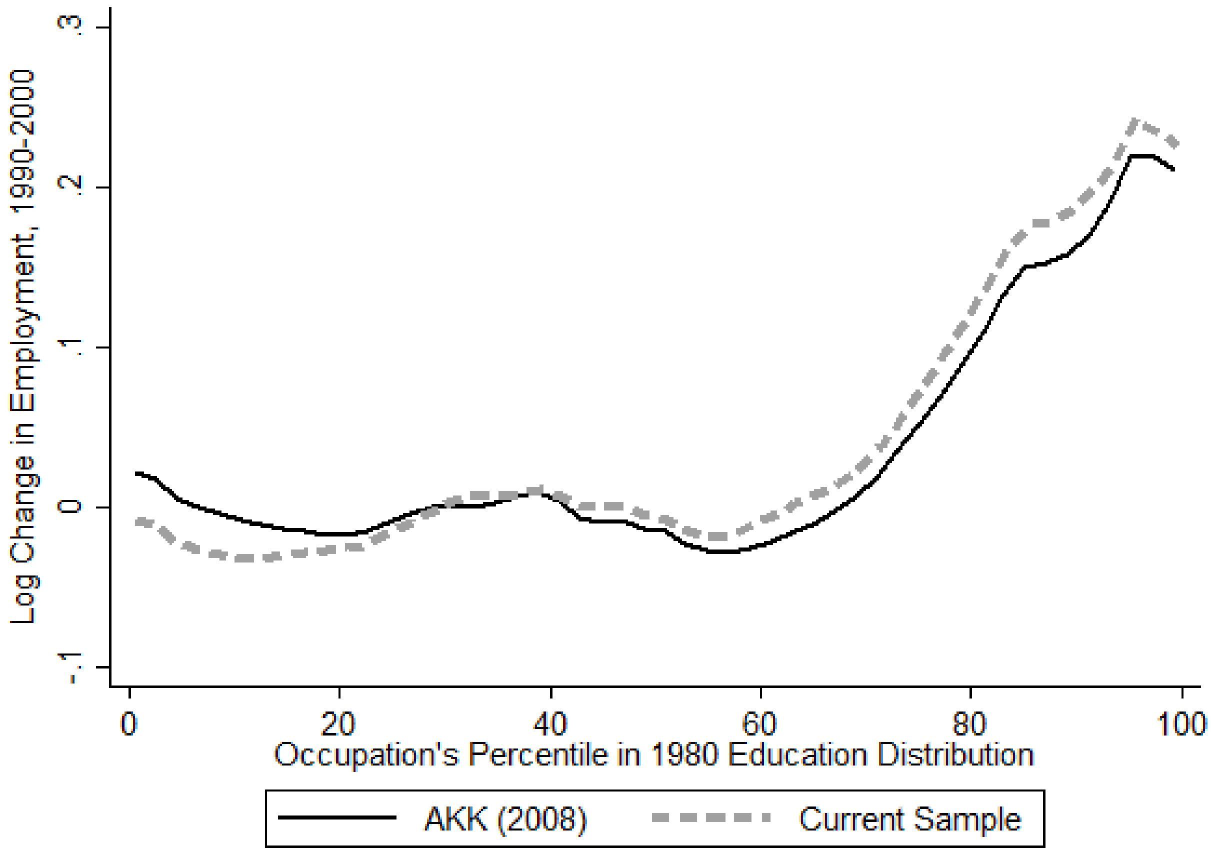


Figure A.4: Smoothed Occupational Employment Growth of *occ1990* Occupations

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

Appendices

A.1 Occupational Employment Growth in 1990s

Although the main indicator for job polarization in the literature is occupational employment changes by occupations' wage percentiles, there are two influential papers (Autor et al., 2006, 2008) in the literature 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 on Autor et al. (2008).

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

Figure A.3 shows the smoothed employment share changes according to two different occupation codes. The upper panel replicates corresponding Autor et al. (2006) and Autor et al. (2008) that shows smoothed 1980-1990 and 1990-2000 changes by means years of education percentiles where occupations are in *occ1990* codes. The lower panel shows the same with *occ1990dd* codes. The comparison between two shows that the particular trend in occupational employment growth during 1990s depends on occupation definitions.[25]

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 section 2, the striking contrast may seem puzzling. For this reason, I compare two coding schemes based on their stability of occupation coverage in Autor et al. (2008)'s data. *occ1990dd* have 330 number of occupations with

[25] As shown in Section 3, however, the long run monotonicity of demand growth is not classification-specific.

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.4 shows smoothed log change of 1990-2000 employment sorted by education percentiles in 1980. In order to see how my own sample compares with theirs I do the exercise both with Autor et al. (2008) data and with the one used in this paper. Although it is true that *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 my data using *occ1990* and the same method, which suggests that differences between the observations of Autor et al. (2006) or Autor et al. (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 (Autor and Dorn, 2013, e.g.,) 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.2 Data Appendix

The data sources and variables are described in Section 2. In this appendix section I describe the details on Census samples used in the paper. 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 bill of an occupation is defined as total annual wage income. Wage income is subject to top-code treatment such that top-coded observations are multiplied by 1.5. Real wages are computed in terms of 2010 dollars and the adjustment is done by PCE index. Real hourly wages are computed as real annual wage income divided by annual hours. For each sample year I assign real hourly wages smaller than the first percentile of wage distribution equal to the first percentile's real hourly wage.

A.3 Theory Appendix

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 β_j. Then, I show that occupational mean wage growth is monotonically increasing in β_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':

$$\left(\frac{h_{jt}}{h_{j't}}\right)^{(1-\rho)} = \left(\frac{d_{j'}\gamma_j}{d_j\gamma_{j't}}\right)\left(\frac{\beta_j}{\beta_{j't}}\right)^{(1-\rho)}\left(\frac{1-\beta_j}{1-\beta_{j't}}\right)^{\frac{\rho-\mu}{\mu}}$$
$$\left(\frac{\left(\frac{\beta_j}{1-\beta_j}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right)^{\frac{\rho-\mu}{\mu}}, \tag{12}$$

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 (10) implies the following for the ratio of high-skill worker to low-skill in occupation j:

$$\frac{H_{jt}}{L_{jt}} = \frac{H_t}{L_t}\left(a_{jj'} + (1-a_{jj'})\, h_{jt} + (a_{ji} - a_{jj'})\, h_{it}\right), \tag{13}$$

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.[26]

In order to characterize the equilibrium allocation, I plug (13) into (12) and express h_{1t} as a function of h_{2t} from the comparison of occupations indexed as 1 and 3:

$$h_{1t} = (1-h_{1t}-h_{2t})\left(\frac{d_3\gamma_1}{d_1\gamma_3}\right)^{\frac{1}{(1-\rho)}}\left(\frac{\beta_1}{\beta_3}\right)\left(\frac{1-\beta_1}{1-\beta_3}\right)^{\frac{\rho-\mu}{\mu(1-\rho)}}$$
$$\left(\frac{\left(\frac{\beta_1}{1-\beta_1}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{21}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_3}{1-\beta_3}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{21}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right)^{\frac{\rho-\mu}{\mu(1-\rho)}}.$$

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

[26]Note that given relative skill supply in an occupation, relative skill supply for any other occupation can be obtained simply by equation (10).

decreasing in h_{2t} while $0 < h_{2t} < 1$.

In the same way, h_{2t} can be written as a 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 (13), within the unit square there exists a unique equilibrium allocation. Here the assumption on the ordering of the βs 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 (12), $\frac{h_{2t}}{h_{3t}}$ decreases too. From (13) it is clear that $\frac{H_{1t}}{L_{1t}}$ increases which, together with skill-biased technology growth, (12) 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 (12) 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 β. Equation (10) suggests that the same holds for low-skill employment. Hence, occupational employment growth and consequently employment share change is an increasing function of β_j.

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

$$\frac{w_{jt}}{w_{j't}} = \left[\frac{d_j}{d_{j'}}\right] \left[\frac{\left(\frac{H_{j't}}{L_{j't}}\right) + 1}{a_{jj'}\left(\frac{H_{j't}}{L_{j't}}\right) + 1}\right] \left[\frac{a_{jj'}\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu} + 1}{\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu} + 1}\right] \tag{14}$$

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 $a_{jj'} > 1$.[27] The last term in the brackets is also increasing since the numerator grows faster than denominator

[27] This follows (13) as a result of the reallocation of high-skill workers towards more skill intensive occupations.

$(a_{jj'} > 1)$.[28]

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 β_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 (14) 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 converge to 1 as the skill intensity goes to zero from above. The last term in brackets converges to a_{21}.[29] Hence, there exists d_1 high enough to ensure $w_{2t}/w_{1t} < 1$ for given time t. Similarly, inspecting equation (14) 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.

□

[28]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 (12).

[29]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.