Welfare Effects of Polarization: Occupational Mobility over the Life-cycle *

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Abstract

The U.S. labor market has experienced polarization over the past several decades, where employment and wages of middle-class individuals have declined relative to those of low- and high-skill groups. What are the welfare effects of such a structural change? We build a full-blown overlapping generations model of individuals who choose consumption, savings, labor supply, and occupations over their life-cycles, and accumulate human capital, as they face uncertainty about labor productivity and longevity as well as the probability of exogenous separation from their current occupations. The model is parameterized to account for life-cycle patterns of occupational distribution and mobility in the early 1980s. We simulate a wage shift as observed in the data during the following decades, investigate individuals' responses, and quantify welfare effects across heterogeneous groups of individuals. Polarization is shown to improve welfare of young individuals that are high-skilled, while it hurts low-skilled individuals across all working ages and especially younger ones. The gain of the high-skilled is larger for generations entering in later periods, who can fully exploit the rising skill premium. We also evaluate changes in inequality and show how polarization leads to a rise in skill premium, increasing inequality in life-cycle earnings and wealth across individuals.

Keywords: Occupational choice and mobility, routine-biased technological shock, overlapping generations model, polarization, welfare effects.
JEL Classification: E24, J21, J24, J62

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1 Introduction

The polarization in the labor market observed during the past several decades generated a peculiar pattern of employment and wage growth. Middle-class workers lagged behind low- and high-skilled workers, resulting in U-shaped growth in both employment shares and wages across skill distribution. A compositional shift in the demand of tasks was shown to be critical in explaining the phenomena by empirical studies such as Autor et al. (2003). Introduction of industrial robots in the manufacturing sector and technological innovations replaced many routine tasks that had been performed by middle-skilled workers. The consequence of this structural change was an erosion of demand for routine workers, as documented by Autor and Dorn (2009), Acemoglu and Autor (2011), Barany and Siegel (2018) and Acemoglu and Restrepo (2018b), among others.[1]

Autor and Dorn (2013) build a model of the goods and services sectors and three types of tasks to show how computerization and replacement of routine tasks lead to polarization in employment and wages. Barany and Siegel (2018) study effects of unbalanced technology shocks and show how a rise in productivity in the manufacturing sector results in an increase in demand for workers in low- and high-skilled services sector that are complements, while driving down demand for and relative wage of manufacturing workers. Acemoglu and Restrepo (2018b) build a task model with directed technical change and endogenous capital, and show that technological change can decrease real wage for some workers, which cannot be accounted for by canonical factor-augmenting technological changes.

Empirical studies clearly identify a group of occupations that are "winners" and "losers" ex post in terms of wages and employment. This fact, however, does not indicate how polarization affects the fate of individuals. A worker engaged in a losing occupation may switch to a winning occupation to exploit differential wage growth. Young workers in a winning occupation may enjoy higher wages for decades throughout their career but others in the same occupation may enjoy the premium for just a few years until retirement. Mobility cost to particular occupations may differ according to the skills or education of an individual and a barrier may be too high for some individuals to overcome. Switching occupations may imply a loss of accumulated human capital for an experienced worker and the need to re-accumulate it for a new occupation. Such a switch may be worthwhile for a young worker but it may not be appealing for an older worker. A move that involves a temporary wage decline may be costly for an individual with little saving but consumption may not be affected for someone else who has enough saving or an access to public insurance.

[1] Acemoglu and Autor (2011) review canonical models with two skill groups and factor-augmenting technology, present a task-based approach that endogenizes substitution of machines for certain tasks to account for recent phenomena in the labor market, including job polarization, and provide a survey of the literature.

Despite a large number of empirical and theoretical studies on routine-biased technological changes and polarization, there are fewer studies focusing on how the shift affects behavior and welfare of heterogeneous individuals. Among various factors, age appears to be one of the critical dimensions in evaluating welfare consequences of polarization.

Acemoglu and Restrepo (2018a) analyze the relationship between a demographic structure and automation and argue that aging is associated with a more pronounced adoption of robots and automation. Abraham and Kearney (2018) study changes in employment by skill and age groups during the last two decades and emphasize roles played by changes in demand factors including the penetration of robots and trade.

Heathcote et al. (2010) build a life-cycle model to study welfare and macro effects of skill-biased technological change on individuals' decisions of education, intra-family labor supply, consumption and savings. Sachs and Kotlikoff (2012) and Benzell et al. (2018) build a two-period life-cycle model with two goods to theoretically investigate roles of a technological shock. They argue that technological innovation benefits owners of the technology and automation can lead to immiserization because young savers with limited skills will own fewer assets. They propose that a proper intergenerational transfer be administered in order to restore productive investment and avoid a decline of capital in the long-run.

Cortes (2016) uses panel data to follow the experience of routine workers and documents their occupational and wage dynamics during decades of polarization. He focuses on how the mobility of employed individuals changes over time, accounting for a shift of occupational distribution.[2] Dvorkin and Monge-Naranjo (2019) build an extended Roy model of a dynamic occupational choice and human capital accumulation. They quantify effects of automation and task-biased technological change on growth and earnings inequality in the U.S. economy since 1980. In their quantitative analysis, they also embed a simple demographic structure, assuming entry of new workers and a stochastic exit in a perpetual youth model. Cociuba and MacGee (2018) construct a search model with three sectors where individuals accumulate sector-specific human capital and own sectoral preferences and analyze how a change in the demographic structure affects sectoral reallocations and the aggregate economy. The model is populated with two generations that age and exit stochastically.

Our model differs from those in the above papers in the following dimensions. We build a full-blown overlapping generations model of individuals that choose occupations while they go through stages of their careers and life-cycles and accumulate physical and human capital. They eventually decumulate the capital as they approach retirement age and choose to exit the labor force. The model accounts for the patterns of occupational choice as part of a set of life-cycle decisions. Working-age individuals are hardly homogeneous and heterogeneity matters in accounting for welfare effects of polarization. We show that

[2] See also Cortes et al. (2017).

quantitative effects differ not only across skills of individuals but also across stages of their life-cycles when the structural change in occupational wages manifests itself.

We use the CPS data to calibrate paths of occupation-specific wages since the early 1980s. We estimate functions that govern human capital accumulation using wage data of individuals that differ in age, education, occupation, cohort, and time. PSID data is used to derive an idiosyncratic component of wage growth that is consistent with the estimated occupation-specific wages and life-cycle profiles of human capital. Our model is calibrated with these life-cycle data and also accounts for the pattern of retirement across different types of workers. The model generates reasonable profiles of assets, consumption and overall earnings across ages and allows individuals to make occupational decisions under tradeoffs faced at different life-cycle stages and under different economic conditions.

We parameterize the economy to approximate the labor market in the early 1980s and then simulate the polarization in this initial economy, a change in the wage structure across occupations that occurred during the following decades. We show that the polarization on average has had positive welfare effects on high-skilled individuals in the initial economy. The high-skilled aged 25 will gain 1.2% in consumption equivalence while the low-skilled of the same age will lose by about 2%. The gain of the high-skilled is larger for generations that enter the economy in later periods although it remains in a narrow range and stays at less than 2% in consumption equivalence. The welfare loss for the low-skilled rises more quickly over time. Upward mobility to occupations with rising wages is limited with high mobility cost and many will choose to accept lower wages. As a generation, future generations fare worse. Note that this is not because the gain of the polarization accrues to the old while sacrificing welfare of the young, but because the welfare loss of the low-skilled rises more rapidly. The high-skilled continues to gain. Different experiences across skill types through evolution of their occupations leads to a rising skill premium and more inequality in earnings and wealth.

The paper is organized as follows. Section 2 presents data used in the analysis and reviews the labor market trends and polarization in employment and wage across occupation categories during the past several decades. We also review cross-sectional trends of employment shares and wages across age groups and investigate employment mobility and wage growth of individuals. Section 3 presents our life-cycle model of occupational mobility and section 4 discusses parametrization of the model. Section 5 presents numerical results and 6 concludes.

2 Data and Trends in the Labor Market

2.1 Data

This section documents the polarization in the labor market in the US over the past several decades. The data source of our analysis is mainly CPS data for occupational distribution and wage profiles, and is supplemented by PSID data for wage growth.

2.1.1 CPS Data

Selection of Individuals: The main data source for our analysis is the Current Population Survey (CPS) from 1983 to 2018, and we use employment and wage data of male heads of household aged at and above 25. We use the labor market data since the early 1980s to capture the long-run polarization trend that continued during the last several decades. We let our sample data start in 1983 because of a known discrepancy in CPS occupational categories between the time before and after 1983, as documented in Kambourov and Manovskii (2013).

Employment Status and Occupational Distributions: Individuals are either employed or not employed, and the employed are divided into groups according to their occupations. To construct occupation categories, we use the 3-digit occupation codes of the Census and categorize them into three groups: Abstract, Routine, and Manual, following Acemoglu and Autor (2011).[3] Occupations are classified as follows.

- **Abstract**: managers, management-related, professional specialty, technicians and related support
- **Routine**: construction trades, extractive, machine operators, assemblers, inspectors, mechanics and repairers, precision production, transportation and material moving occupations, sales, administrative support
- **Manual**: housekeeping, cleaning, protective service, food preparation and service, building, grounds cleaning, maintenance, personal appearance, recreation and hospitality, child care workers, personal care, service, health care support

For non-employment, we exclude those who report unemployed as their employment status. As we will discuss below, the frequency of our model is annual and the model is not built to account for in-and-out labor market mobility of a high frequency and, in particular, frictional unemployment of a short duration, which represents most unemployment

[3] We use the 1990 SOC codes of the CPS.

incidences.[4] Such unemployment would not necessarily involve major depreciation of human capital, mobility to another occupation as a result, or a permanent exit from the labor force.

We identify from data and distinguish between short-term unemployed (less than or equal to 3 months) and long-term unemployed (more than 3 months), and include the former as employed based on the occupation that the individual reported he was engaged in during his previous job.[5]

Hourly Wage: Hourly wage is computed as the sum of wage and business income of an individual divided by work hours. Following Baum-Snow and Neal (2009), in the computation of wages, we drop samples that report weekly hours of less than 5 hours and whose computed hourly wage is less than \$1.5. Also, we drop those whose hourly wage is greater than \$99.8 in 1999 dollars.

2.1.2 PSID data

The data source to estimate idiosyncratic income shock is the Panel Study of Income Dynamics (PSID) from 1983 to 1997. We limit samples to male household heads aged 30 to 59 and employed in either three occupation categories of abstract, routine, and manual to be consistent with CPS data. We exclude the oversample of low-income households (SEO samples) and the immigrant samples.[6] We document the detailed procedure of the estimation in section 4.[7]

2.2 Polarization in the Labor Market

This section reviews and documents polarization in the labor market in the US over the past several decades. The data source is CPS data.

[4]Among our unemployed male-head CPS samples (since 1968, those aged between 25 and 64), the average elapsed duration of unemployment was 16 weeks and the median 11 weeks.

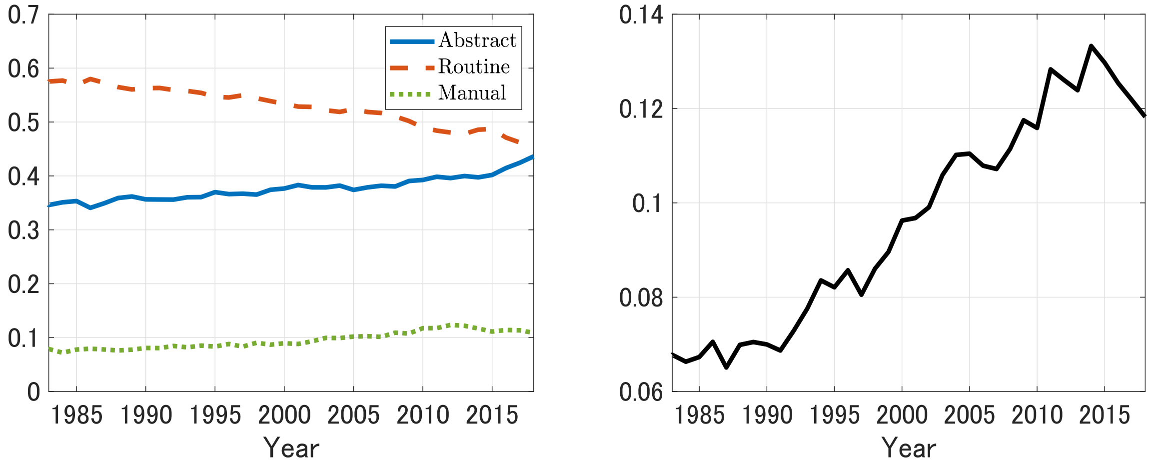
[5]We also drop samples that are unemployed for less than or equal to 3 months but fail to report their previous occupations. We note that there is no major change in the occupational distribution when we adjust the cutoff from 3 months to 6 months or 12 months.

[6]Consistent with our treatment of the CPS data, when computing wages, we drop samples that report weekly hours of less than 5 hours and whose computed hourly wage is less than \$1.5 or greater than \$99.8 in 1999 dollars, following Baum-Snow and Neal (2009).

[7]We use the PSID data only for calibration of idiosyncratic income shock. We could have used PSID data for occupational mobility. However, CPS data and PSID data are not entirely compatible, and occupational distributions are different as documented in Kambourov and Manovskii (2013). Thus, we choose to use a variable in the CPS, `occly`, which reports the person's primary occupation during the previous calendar year. See section 4 for more details.

Macro Dynamics of Employment and Wage: Figure 1a shows the distribution of workers aged 30-59 across the three occupation groups from 1983 to 2018. A share of the routine occupations, which employed approximately 60% of the workforce in the early 1980s, has fallen steadily to 45% in 2018. Employment shares of both abstract and manual occupations absorbed the decline and rose nearly monotonically during the last several decades. Figure 2 plots shares of abstract and manual occupations relative to that of routine occupations of the same year, which more clearly indicates a rapid and almost monotone decline of routine occupations relative to the other two.

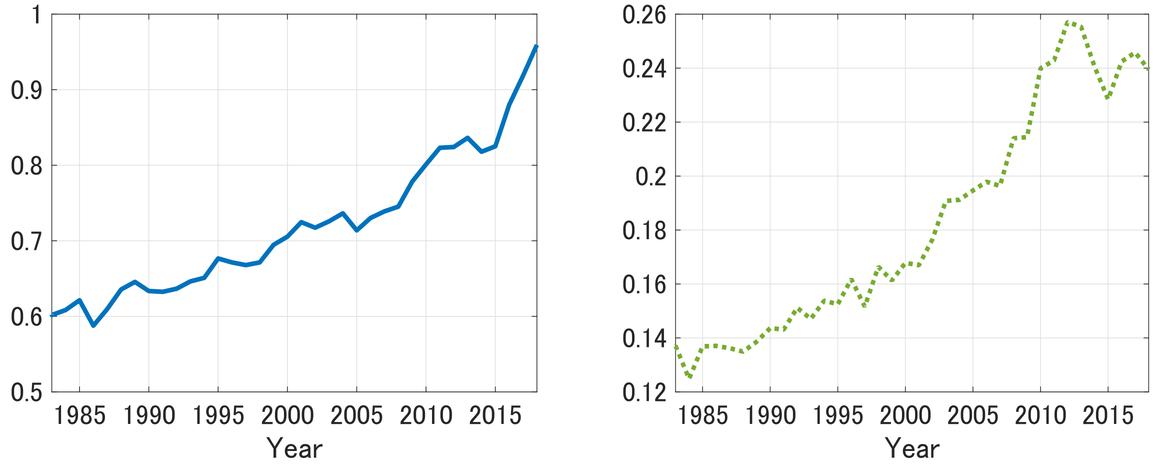
Figure 1b shows the share of non-employment out of all individuals in our sample aged 30-59 in each year. This fourth group includes those not in labor force and full-time students. The non-employment rate of working-age individuals was less than 7% in the early 1980s and increased steadily to reach 13% by the early 2010s.



(a) By Occupation Category

(b) Non-employment Rate

Figure 1: Employment Share and Non-Employment Rate (Age 30-59)

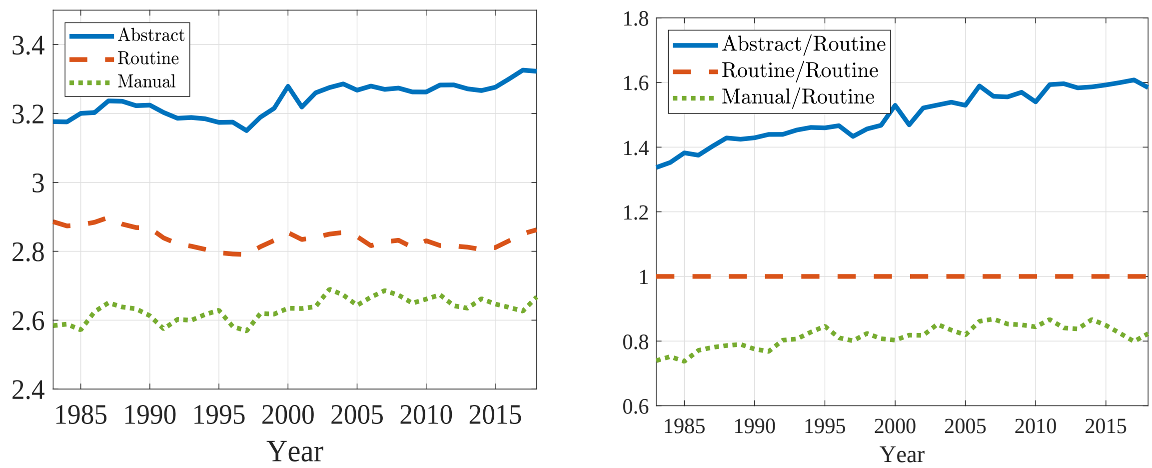


(a) Abstract (b) Manual

Figure 2: Relative Employment Share (Routine=1, Age 30-59)

In tune with employment shares, wages evolved differently across the three occupation categories. The left panel of Figure 3 shows hourly real wage in the three occupations over time. Routine wages declined from the 1980s to the mid-1990s and it have stagnated since 2000. Manual wages have always lain below routine wages, but the difference between the two has declined since the 1980s.

The right panel of Figure 3 shows the dynamics of abstract and manual wages relative to routine wages in each year. While relative wages of manual occupations grow and approach 1 from below, abstract wages have quickly diverged from 1 since the early 1980s, indicating a decline in the relative wage of routine workers against both occupations.



(a) Hourly Wage (in log) (b) Relative Wage (routine=1)

Figure 3: Wages by Occupation Category

Employment and wage data across three occupation categories indicate that the polarization and decline of routine occupations is not a phenomena that occurred during a particular decade or a trend that started recently but it has continued for a much longer period and continuously over the last several decades.[8]

Polarization and Life-cycle: Figure 4 shows an age dimension of the polarization during the past decades, indicating how individuals of different ages have been spread across different occupations and how the distribution evolved since the 1980s.[9] We group individuals of a given age in each year into the four bins of employment types, including employment in the three occupation categories and a state of non-employment, and plot the shares by age on a horizontal axis for each decade from the 1980s to the 2010s.[10]

[8]This is consistent with the argument of recent papers including Barany and Siegel (2018), who argue that the polarization started in as early as the 1950s using the US Census and American Community Survey (ACS) data, and Cortes (2016), who analyzes the PSID data since the 1970s.

[9]We compute shares for a five-year age group in each decade as it helps remove noisy spikes that would make it hard to read the profiles due to a very small sample size in some combinations of age and occupation.

[10]For example, 0.5 in Figure 4b at age 40 in 2000-2009 indicates that 50% of individuals at age 40-44 in 2000s were employed on a routine occupation, while 8% were not in labor force as shown for a corresponding sample in 4d.

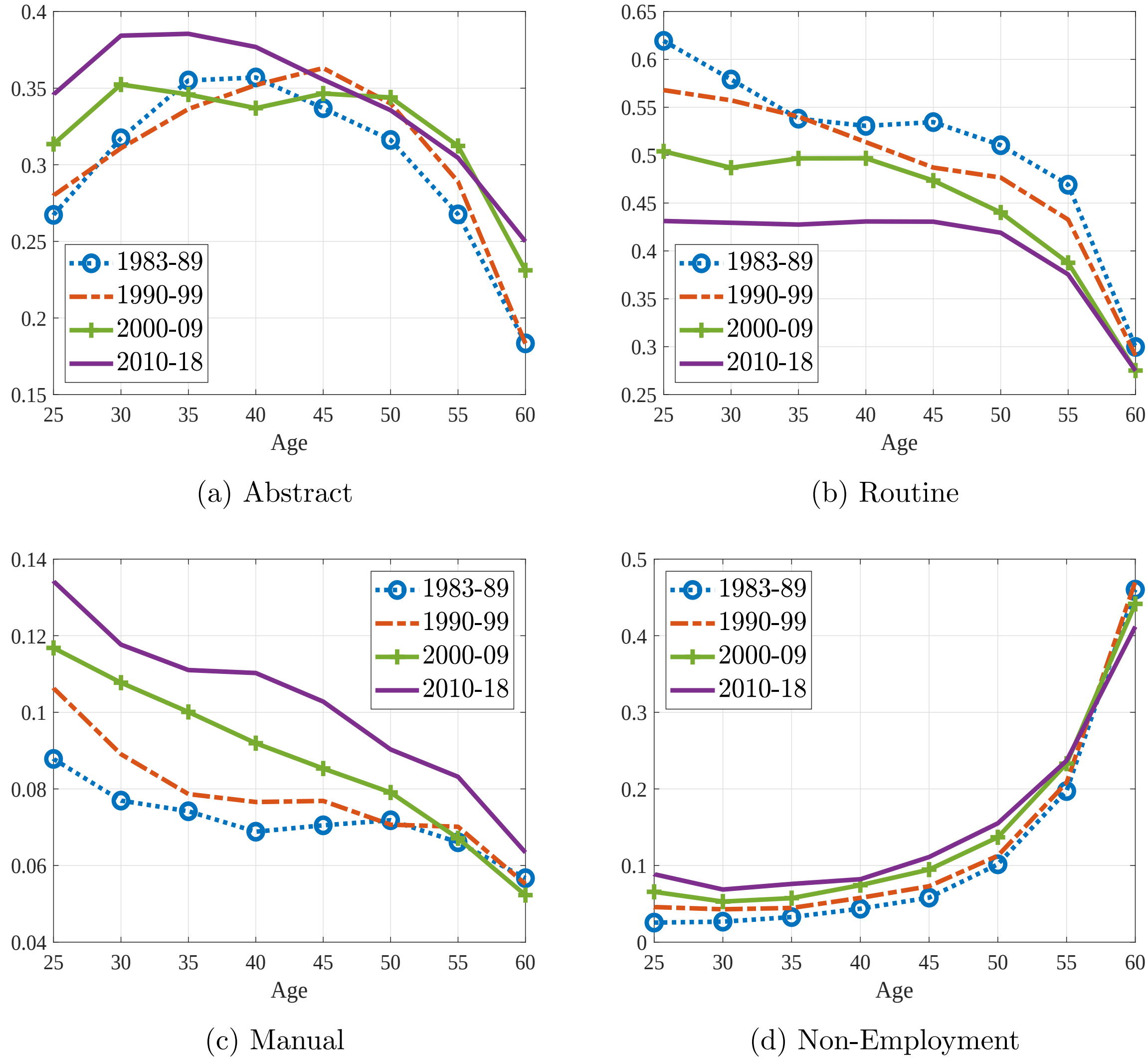


Figure 4: Employment Status by Age (shares of each employment status and occupation within each age group)

Shapes of the profiles are uniquely different across occupation categories. A cross-sectional life-cycle profile of the abstract occupations, as shown in Figure 4a, is mildly hump-shaped in all decades. The share is slightly lower among individuals in their 20s and reaches a peak of 35-38% thereafter. The profiles show a decline well before the retirement age, reaching 18-25% by the early 60s.

The rising trend of the employment share of abstract occupations as seen in Figure 2a is less visible in life-cycle profiles and the increase is not monotone across age groups. During the past few decades, the peak of the share has shifted to a younger age and the share is the highest among those in their 30s in the 2010s, and profiles show a steep decline thereafter as the age increases, indicating the effects of changes across cohorts as we will discuss below.

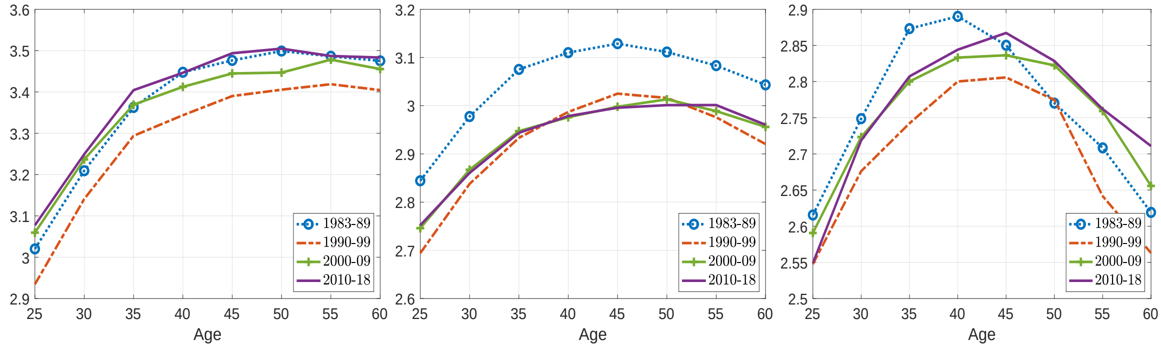
A decline in the employment share of routine occupations is more clearly visible across all age groups, as shown in Figure 4b. From the 1980s to the 2010s, the shares fell by more than 10 percentage points for individuals ranging from their 20s to 40s. The decline is more pronounced among those in the early stage of their lives. For example, the sector declined by about 19 percentage points among those aged 25-29.

Manual shares remain low during this period. Since 1980s, however, the profile started to become more negatively sloped in age while the level increased, implying an increase in the inflow of workers in their 20s into manual occupations as they entered to the labor market.

In addition to the three occupation categories for the employed, we include a fourth state of non-employment in the analysis. As shown in Figure 4d, individuals start to leave the labor force in their 50s, when they have more than a decade before reaching the normal retirement age and starting to collect social security benefits. At the same time, a large fraction of individuals remain in the labor force even in their early 60s and, in fact, in their late 60s and later as well, though the latter is not indicated in the figure.

The share of non-employment has increased since 1980s across all age groups. Non-employment is an important state to include when we analyze labor market mobility of individuals over their life-cycle and across occupations.

Figure 5 shows life-cycle profiles of wages in abstract, routine and manual occupations, respectively during the past few decades. The shapes of profiles are somewhat similar, rising fast during the early phases of careers in their 20s and 30s and slowing down later in their 40s and 50s. The decline in wages in later years is more visible in the routine and manual occupations, but the wages are flatter until individuals are in their late 50s and early 60s in the abstract sector. Abstract wages declined from the 1980s to the 1990s and rose afterwards. Routine wages showed a decline from the 1980s to the 1990s and have stagnated since then, which is consistent with the shift with the aggregate wage transition seen in Figure 3. The decline is particularly large among those in their 20s to mid-40s. Routine occupations of these age groups experienced a significant decline not only in the employment share as we saw in Figure 4 but also in wages.



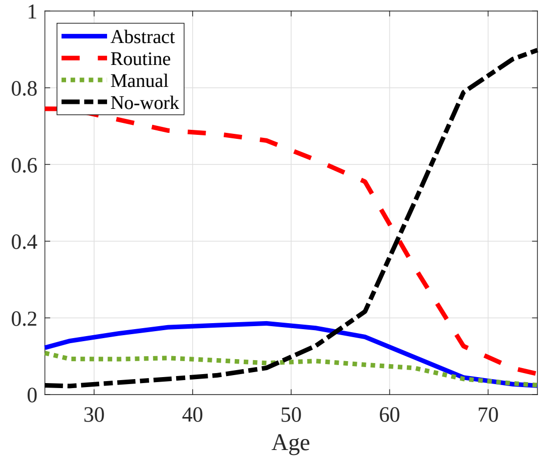
(a) Abstract (b) Routine (c) Manual

Figure 5: Wage by Age (in log)

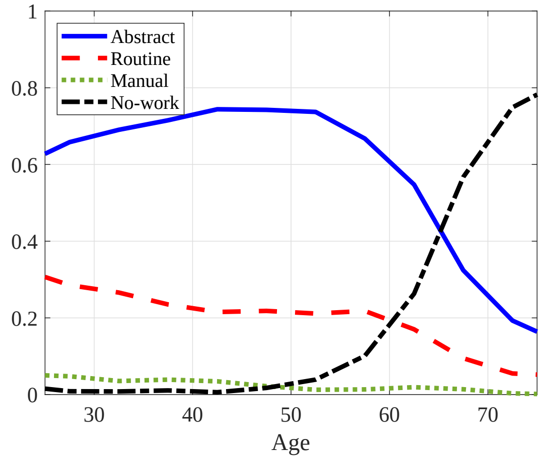
Occupation by Skills: In the quantitative model we build below, we also divide individuals by skills, distinguishing between those with and without college education. The distinction is motivated by their very different patterns of occupations over their life-cycles.

Figure 6 shows a life-cycle profile of occupations by skills according to CPS data in the early 1980s (1983-1985). Low-skilled workers are predominantly engaged in routine occupations throughout their life-cycle and the high-skilled are most likely to be engaged in abstract jobs. 10-20% of low-skilled workers are engaged in abstract jobs from their 20s to 60s, while about 20-30% of high-skilled workers assume routine occupations. Manual occupations constitute a very small fraction of both types of workers, though there are relatively more of them among low-skilled than high-skilled individuals.

Low-skilled workers tend to leave the labor force earlier than the high-skilled and participation rates at age 65 are about 35% among our low-skilled samples, whereas it is as high as 60% among the high-skilled.



(a) Low-skilled



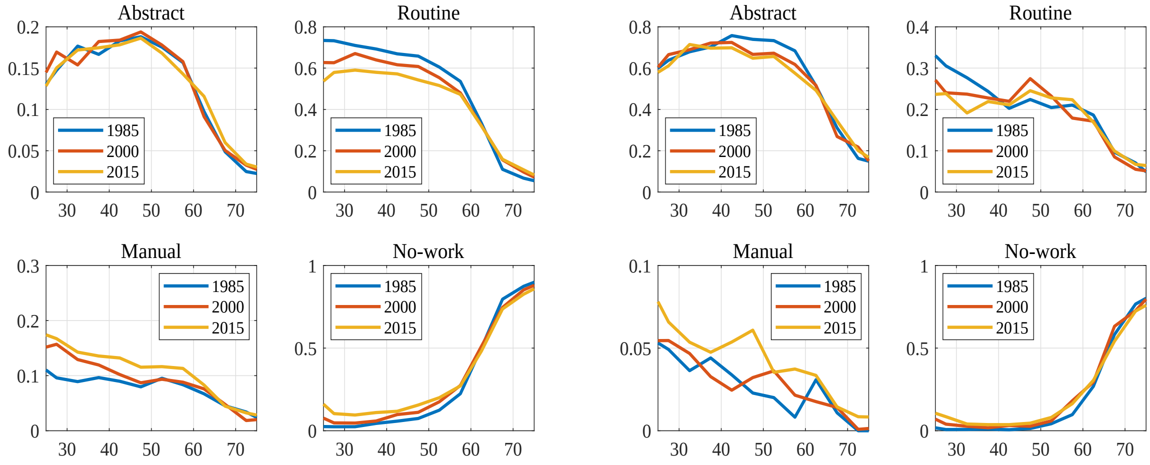
(b) High-skilled

Figure 6: Occupation by Age and Skills (CPS Data in 1983-1985)

Figure 7 shows how the distribution shifted over time using cross-sectional distribution for the selected years of 1985, 2000 and 2015.[11] Although the share of workers in abstract occupations rose monotonically at the aggregate level as we saw in Figure 1, the share has not increased or even changed much conditional on age and skills. The seemingly puzzling discrepancy is explained by a rise in skills of new entrants, as shown in Figure 8. The share of high-skilled individuals, a large fraction of whom are in abstract occupations, increased from around 30% in the early 1980s to more than 40% by the late 2010s, with some non-monotonicity during the transition.

The share of routine occupations has decreased across all ages among the low-skilled, who constitute the majority of the occupation. Manual occupations have also increased relative to other occupations, although changes are not monotonic among the high-skilled. These figures emphasize the importance of taking into account heterogeneity in skills and phases of life-cycle in quantifying welfare effects of polarization that occurred during the last decades.

[11]Similar figures can be generated for life-cycle profiles of different cohorts, rather than in the cross section. The main observations about the occupational trend remain the same and we do not include them in the paper to save space.



(a) Low-skilled (b) High-skilled

Figure 7: Occupation by Age and Skills over Time (CPS Data in 1985-2000-2015)

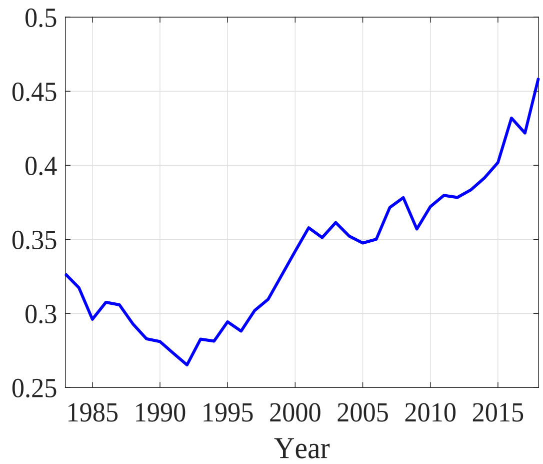


Figure 8: Fraction of High-skilled (CPS Samples Aged 25-29 in 1983-2018)

3 Model

This section describes elements of the model and individuals' life-cycle problem.

Demographics: At age $j = 1$, individuals enter the market with initial assets denoted as a_1. ϕ_{j+1} represents the conditional survival probability that individuals aged j remain alive until age $j + 1$. We assume that individuals die with certainty at the end of age $j = J$ and $\phi_{J+1} = 0$ by assumption.

Endowment, Occupation and Human Capital: Individuals are born with a skill type, $s = \{L, H\}$, which represents their education prior to entry into the labor market.

A state variable, o, summarizes employment status and an occupation of a worker, that is, $o = \{A, R, M, N\}$, where the last element N denotes a state of non-employment. The employment status is an individual's choice and evolves endogenously over the life-cycle. Workers are employed in one of the three occupations: abstract, "A," routine, "R," and manual, "M."

Earnings of an individual of skill s, in occupation o, at age j and time t is given as $y_{t,j,s,o} = \eta_{s,o} h_{j,s,o} w_{t,o} l$. Here, $\eta_{s,o}$ denotes an idiosyncratic labor productivity shock and $h_{j,s,o}$ is human capital. $w_{o,t} \in \{w_{A,t}, w_{R,t}, w_{M,t}\}$ is occupation-specific wage and l is an indicator for participation and equals 1 if $o = \{A, R, M\}$ and 0 if $o = N$.

Workers accumulate occupation-specific human capital on the job. Human capital of an individual of age j and skill s evolves according to function $h' = f^h(h, j, s, o, o')$, where o' denotes his occupation in the next period. Human capital grows endogenously with the decision of participation and occupation. Initial human capital at age $j = 1$ is given as $\overline{h}_{1,s,o}$ for each skill type and occupation.

There are two types of shocks that affect earnings of individuals. First, an individual of skill s and occupation o faces an exogenous separation from his current occupation with probability $\lambda_{s,o}$. Upon receiving the separation shock, the individual will have a choice of leaving the labor force or choosing another occupation in the following period. The occupation-specific human capital he has accumulated will be lost.

Second, an individual of skill s draws a vector of idiosyncratic productivity shock $\overline{\eta}^s = \{\eta_A, \eta_R, \eta_M\}$ from skill-specific distribution in each period.

Preferences: Individuals derive utility from consumption and disutility from labor participation, and a period-utility function is denoted as $u(c, l)$. β is the subjective discount factor.

When individuals change occupations, they incur a mobility cost of $c^s_{oo'}$ in terms of lost utility, which depends on skill level s as well as the occupational origin o and destination o'.

Social Security and Transfers: Individuals receive social security benefits once they reach the eligibility age j_R. We assume that the payment is constant at ss. The government also operates a means-tested transfer program which guarantees a minimum level of consumption $\underline{c}$ and the amount of the transfer is given as $\max\{0, \underline{c} - (1+r)a - ss\}$.

The total transfer payment from the government including social security benefits and a means-tested transfer is denoted as tr, which depends on the set of individual states, as explained below in the life-cycle problem of an individual.

Life-cycle Problem: A state vector of an individual is given by $x \equiv \{j, a, s, o, h\}$, where j denotes age, a assets, s skill, o occupation, and h human capital.

We solve the problem of an individual in two steps, using two value functions, V and W. The former, V, is determined by participation and occupation decisions, subject to shocks to productivity and changes in human capital as a consequence of his occupation decision. The latter, W, is determined by consumption and saving decisions.

As an individual enters a new period, he learns whether he is subject to separation shock $\lambda_{s,o}$ or not. At the same time, he draws a vector of idiosyncratic productivity $\overline{\eta} = \{\eta_A, \eta_R, \eta_M\}$ that would affect his earnings in each occupation o'.[12] Based on the information, he will choose a new occupation. The choice will affect his new human capital h', which is occupation-specific, and the occupational choice will take into account the evolution of human capital, as shown in the following Bellman equation.

$$\begin{aligned} V(j,a,s,o,h) &= \int_{\overline{\eta}} \lambda_{s,o} \max_{o'(\neq o)} \{W(j,a,s,o',h',\eta_{o'}) - c^s_{oo'}\} \\ &\quad + (1-\lambda_{s,o}) \max_{o'} \{W(j,a,s,o',h',\eta_{o'}) - c^s_{oo'}\} \, d\overline{\eta} \end{aligned}$$

where $h' = f^h(h,j,s,o,o')$.

Next, given a new occupation o' as well as productivity $\eta_{o'}$, which is occupation-o' specific, and a new level of human capital h', an individual chooses consumption c and savings for the next period a'. $tr(x)$ denotes a transfer from the government which includes a means-tested transfer as well as old-age social security benefits and depends on a state vector of an individual.

$$\begin{aligned} &W(j,a,s,o',h',\eta_{o'}) = \max_{c,a'} \{u(c,l) + \beta\phi_{j+1} V(j+1,a',s,o',h')\} \\ &\text{s.t.} \\ &a' + c = (1+r)a + h'\eta_{o'} w_{o'} l + tr(x) \end{aligned}$$

Note $l = 1$ if $o' = \{A,R,M\}$ and 0 if $o' = N$.

4 Calibration

Preliminaries: We use the model described above to quantify effects of polarization on individual decisions and welfare. We will first calibrate the model to an initial economy that approximates the distribution of individuals across occupations and labor market in the early 1980s. We will then introduce "polarization" that changes the paths of occupation-specific wages, as well as the distribution of new entrants across occupation and skills as we will discuss in more details below.

[12]Note that if he is separated from current occupation o, he is unable to stay in the same occupation in the following period and the draw of η_o is irrelevant.

The model frequency is annual. We let individuals enter the economy at age 25 and live up to a maximum age of 85 ($j = 1, \cdots, 61$). Survival probabilities ϕ_j are based on the U.S. life table of 1990. The interest rate is assumed constant and set to 4%.

Endowment, Productivity and Wages: Skills are represented by education levels which are determined prior to the entry of individuals into the labor market. We assume that individuals start their life with zero initial assets, $a_1 = 0$.

We let individuals of given skills draw a set of initial productivity and initial occupations from skill-specific distributions. In particular, the idiosyncratic productivity η is drawn from a stationary distribution of η shocks for each occupation. Occupation-specific wage in year t, $w_{o,t}$, is computed from CPS data. We explain a detailed calibration procedure after discussing calibration of human capital below.

Human capital: The level of human capital at the initial age for each skill and occupation is given by $\overline{h}_{1,s,o}$, which is the average wage of individuals aged 25 of different skills and occupation based on the age-specific wage profiles we estimate using CPS data, as presented below.

After entry, the level of an individual's human capital evolves according the law of motion $h' = f^h(h, j, s, o, o')$, which depends on the individual's age, current human capital, skills and new and old occupations.

When an individual continues to work in the same occupation, his human capital grows at rate $g^h_{j,s,o}$, which depends on his age, skills and occupation. When he moves to a new occupation, he would lose occupation-specific human capital that he has accumulated and need to accumulate human capital in the new occupation o', starting from an entry level of human capital, $\overline{h}_{1,s,o'}$. Note that, however, his earnings do not necessarily fall due to such an occupational transition since they also depend on an occupation-specific wage rate that varies over time and idiosyncratic component.

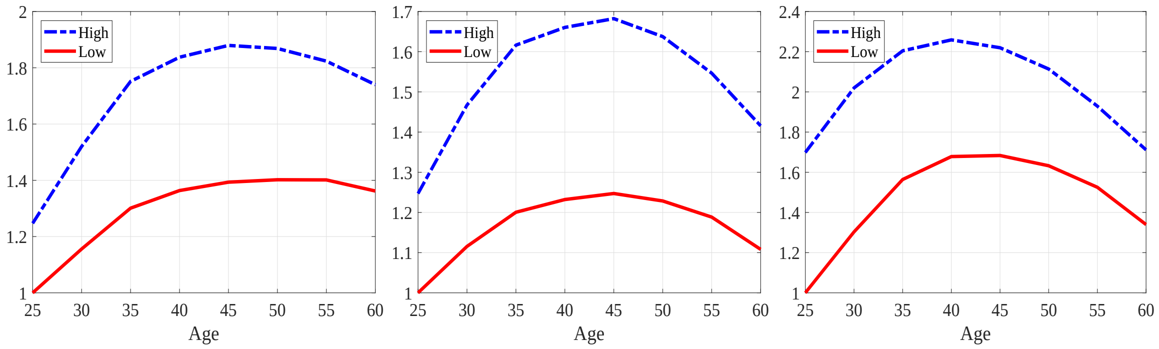
The law of motion for human capital $h' = f^h(h, j, s, o, o')$ is given as follows.

$$h' = (1 + g^h_{j,s,o})h \text{ if } o' = o$$
$$h' = \overline{h}_{1,s,o'} \text{ if } o' \neq o$$

Three components related to earnings, first, idiosyncratic shock process for η, second, human capital dynamics, and third, occupation-specific wage paths, are calibrated with CPS data. We use wage data $w_{i,j,s,o,t,\tau}$ in year t of individual i of age j, skill s, occupation o, and cohort τ and decompose the series into the three components. We describe the calibration process in four steps.

First, we regress the wage data on age, occupation, skill, cross terms of age and occupation, cross terms of age and skill, year dummies, cohort dummies, and cross terms of year dummies and occupation.[13] As is well known, including full vectors of time-related dummies of age, year, and cohort would generate collinearity. Following Aguiar and Hurst (2013), we attribute wage growth to age and cohort effects and use year dummies to capture cyclical components.

Second, we extract average predicted values for each age, skills and occupations to compute age-wage profiles for each combination of skills and occupations. Figure 9 shows the lifetime path of average human capital for each skill and occupation, where we normalize estimates by the average wage of low-skilled workers aged 25-29for each occupation.[14] The growth rate of human capital $g^h_{j,s,o}$ is computed as the age-derivative of these profiles.



(a) Abstract (b) Routine (c) Manual

Figure 9: Estimated Lifetime Human Capital (Low, aged 25/29=1)

Third, we calibrate occupation-specific wage rate $w_{o,t}$ by averaging predicted values for each occupation in year t. Figure 10 shows the path of estimated occupation-specific wage in log from 1983 to 2018. We normalize the profile by wages of routine occupations in each year. Note that these profiles are different from the simple average wage age profiles computed for all workers of each occupation in Figure 3. The latter profiles do not take into account heterogeneous human capital that varies by age while the former do. The trend, however, that both abstract and manual occupation wages grow faster than those of routine occupations during this period remains unaffected.

[13]We use age dummies for a five-year age group in each year as it helps remove noisy spikes that would make it hard to read profiles due to a very small sample size in some combinations of age and occupation.

[14]We assume that the path is time-invariant. As shown in Figure 5, this assumption may well be justified for workers in abstract or routine occupation. For manual occupation, the lifetime path of the 1980s is slightly different from those in other periods. We assume a time-invariant path since the differences are quantitatively small, and the effects of an alternative assumption would be small from a macro perspective, because the share of manual occupations accounts for less than 10% of the population as shown in Figure 1.

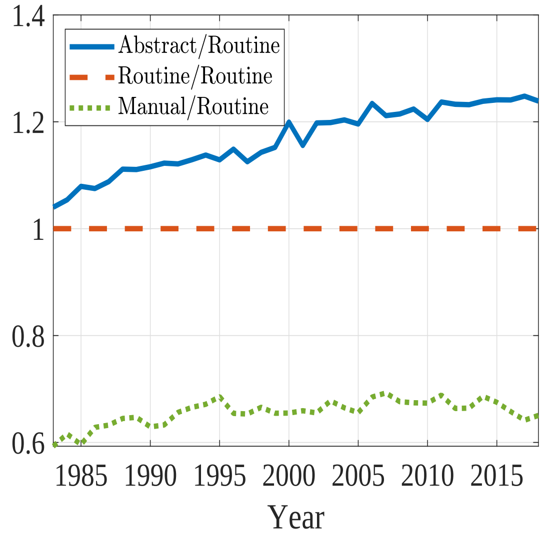


Figure 10: Estimated Occupation-Specific Wage $w_{o,t}$ (Routine=1)

Finally, we calibrate idiosyncratic shock η, estimated from residuals of log-wage after removing average age-specific human capital and occupational-specific wage rates estimated in above steps. Since we need panel data for the estimation of wage growth, we use PSID data from 1983 to 2018 in this step. The standard deviation of the i.i.d. shock is 0.18 for wages of all occupations and we use this value to calibrate the draws of η.[15]

Preferences: We assume the period utility function

$$u(c,l) = \frac{c^{1-\gamma}}{1-\gamma} - B_s \cdot l,$$

and that an individual derives utility from consumption and incurs disutility from work B_s, if $l = 1$. We set the values of disutility so that the model matches average participation rates of 35% and 60% at age 65 for low- and high-skilled individuals, respectively. γ represents the degree of risk aversion and is set to 2.0. The subjective discount factor β is set at 0.982, calibrated to match the ratio of average wealth (for the poorest 99%) to average pre-tax earnings, at 3.9.[16]

We calibrate the occupational switch cost $c^s_{oo'}$ $(o = N)$ together with other parameters related to occupational mobility and discuss them in the next paragraph.

Occupational mobility: We use CPS data to calibrate two sets of parameters that are closely tied to mobility across occupations: first, probabilities of exogenous separation $\lambda_{s,o}$ and occupational mobility cost $c^s_{oo'}$.

[15] We also estimated the standard deviation for each occupation and for each combination of occupations and skills. The values for the former lie in the range from 0.17 to 0.24. We choose to use the average across occupations since some groups, for example a group of high-skilled manual workers, has a very small number of samples and estimates are not very reliable.

[16] Heathcote et al. (2010) use the 1992 SCF and report the average wealth to earnings ratio of 3.94.

Our model accounts for an individual's exit from the labor force associated with a transition from a working phase to retirement. We do not, however, account for various reasons behind non-employment among young individuals, for example, due to health and disability shocks, or full-time study. Therefore, we assume that mobility from employment to non-employment is due to retirement and that employment status N is an absorbing state.

We use a variable, `occly`, of the CPS that indicates an occupation of an individual in the previous year, and construct a transition matrix across three occupations. We use mobility data of workers aged between 30 and 49 over the three years from 1983 to 1985 to approximate mobility of active workers in the initial economy. The transition probability is given in (1) and (2) below. $p^s_{oo'}$, the $\{o, o'\}$-th element of the transition matrix, denotes the probability that a worker of skill s moves from occupation o in the current period to o' in the next period.

$$\begin{array}{ccc} & & \begin{array}{ccc} A & R & M \end{array} \\ \text{Low} & = & \begin{array}{c} A \\ R \\ M \end{array} \left[\begin{array}{ccc} 0.967 & 0.029 & 0.005 \\ 0.008 & 0.986 & 0.006 \\ 0.009 & 0.047 & 0.944 \end{array} \right] \end{array} \tag{1}$$

$$\begin{array}{ccc} \text{High} & = & \begin{array}{c} A \\ R \\ M \end{array} \left[\begin{array}{ccc} 0.987 & 0.012 & 0.001 \\ 0.036 & 0.961 & 0.003 \\ 0.042 & 0.040 & 0.919 \end{array} \right] \end{array} \tag{2}$$

For calibration of mobility cost $c^s_{oo'}$ across occupations, we make the following assumptions. First, we assume that individuals do not transition from manual occupations to abstract occupations directly and set $c^s_{MA} = \infty$ for all s. We make this assumption given the very small number of workers making such a transition.[17] Besides the move from M to A, we assume that mobility cost in all other directions is zero except for moves from M to R and from R to A, which involve an upward change in occupation-specific wages. We calibrate mobility cost c^s_{RA} to match an average share of abstract occupations and mobility cost c^s_{MR} to match transition probabilities p^s_{MR} for each skill type $s = \{L, H\}$ in the initial economy.

We calibrate probabilities $\lambda_{s,o}$ of exogenous separation so that the model matches total separation rates from each occupation and skill as shown in the transition matrices above for our initial economy.

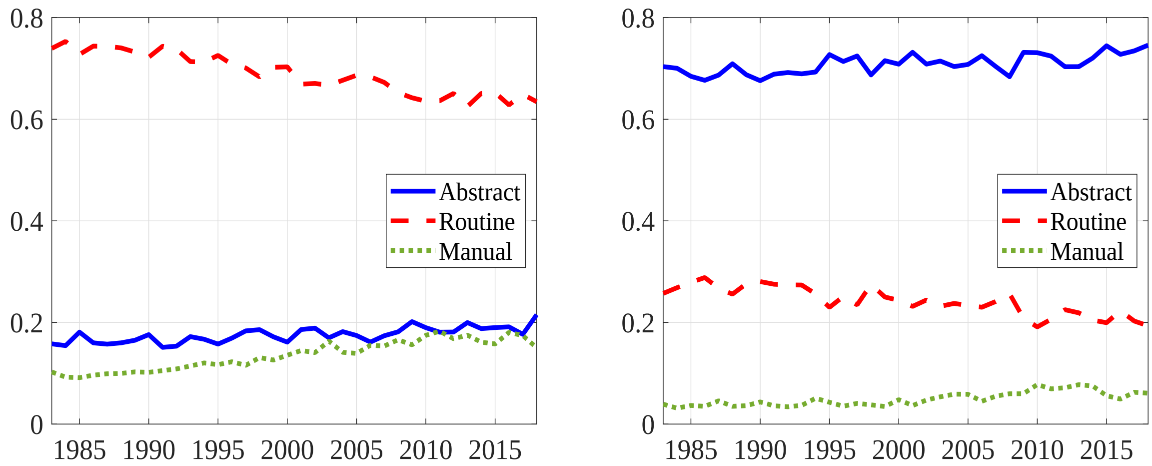
Government: The consumption floor $\underline{c}$ is set to 10% of average earnings in the initial economy. Annual social security benefits ss are provided to individuals once they reach

[17] p^L_{MA} is less than 1% and although p^H_{MA} is larger at 4.2%, the number of such moves is extremely small given that very few high-skilled individuals of this age group work in manual occupations in the first place.

age 66 ($j = 42$). The amount is set so that benefits replace 38% of average earnings in the initial economy. Both the level of the consumption floor and pension benefits are fixed throughout the transition. Accidental bequests are assumed to be confiscated by the government and used for public expenditures that do not affect individuals' budget constraint or preferences.

Other Variables in Transition: As explained above, entrants of age $j = 1$ are randomly assigned to initial occupations, based on the CPS distribution. We use data of occupational distribution of workers of each skill type aged between 30 and 34.[18] Figure 11 shows occupational distribution between 1983 and 2018. Not surprisingly, as already seen in Figure 7, there is no major change in the share of abstract occupations in both low- and high-skilled workers and it rises only very mildly over the last decades. There is a more visible increase in manual occupations and a decrease in routine occupations. We use a smoothed version of the paths as the initial distribution for entrants in the transition computation.

The time path of skill distribution is based on CPS data, as we already saw in Figure 8. This does not affect the optimization problem of individuals, but is relevant when we compute cohort-specific welfare effects of polarization as it is used as a weight on each skill type within a cohort.



(a) Low-skilled (b) High-skilled

Figure 11: Distribution of Initial Occupations

[18]We use data of those aged 30-34 in 1983 to 2018, rather than those aged 25-29 or younger, to account for changes in the initial distribution. The model does not account for worker mobility in the very early phase of a career, which involves frequent occupational switches and churning, for various reasons that we do not capture by the features of our model.

Table 1: Parameters of the model: initial economy

Parameter	Description	Values, source and target
Demographics		
$\{\phi_j\}_{j=1}^{J}$	conditional survival probabilities	SSA Life Table (1990)
J	maximum age	61 (85 years old)
μ_s	skill distribution (H and L)	CPS data
Preference		
β	subjective discount factor	0.982
		average wealth-income ratio of 3.9
γ	curvature parameter	2.0
B_s	cost of labor force participation	$\{0.36, 0.59\}$
		CPS participation data (age 65)
$c_{oo'}^{s}$	occupational mobility cost	CPS mobility data (age 30-49)
$\underline{c}_{o}^{s}$	occupational entry cost	CPS occupation distribution (age 25-29)
Labor productivity and human capital		
$g_{j,s,o}^{h}$	human capital growth rate	CPS life-cycle profile (estimated)
$h_{1,s,o}$	initial human capital	CPS life-cycle profile (age 25-29, estimated)
η_o ($\sigma_{\eta,o}$)	idiosyncratic productivity shock	0.18
		PSID wage data (residual, estimated)
$\lambda_{s,o}$	separation shock	CPS mobility data (age 30-49)
Factor prices: wages and interest rate		
r	interest rate	4%
w_o	wage rate by occupation	CPS data (estimated)
Government		
$\underline{c}$	consumption floor	10% of average earnings
ss	social security for retirees	average replacement rate of 38%

5 Numerical Results

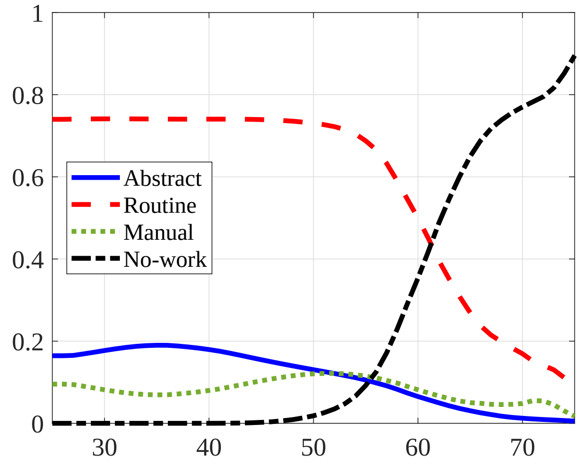
In this section we first present the numerical results for the initial economy. We then discuss the transition dynamics after the economy experiences polarization. Finally, we analyze welfare effects from polarization and compare impact on individuals of different skills, ages and cohorts.

5.1 Initial Economy

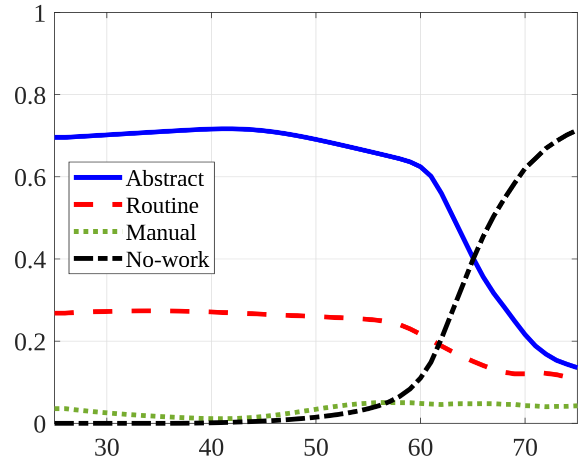
Figure 12 shows occupation shares by age for low- and high-skilled individuals, respectively. The data counterpart of this figure is Figure 6 in section 2. The match is successful partly because of the calibration strategy where we set certain parameter values to match key moments in the data.

The initial occupations are randomly assigned so that the distribution is consistent with the CPS data. We also restrict upward occupational mobilities, for example, from manual to abstract and from routine to abstract occupations, by calibration of mobility cost so that the overall transition is consistent with the data. Also, a preference parameter that represents participation cost for each skill type is set to match the average participation rate at age 65. Other than these parameters, moves from one occupation to another and transitions from work to retirement are endogenously chosen by individuals, while they also choose optimal consumption and savings and accumulate human capital over their life-cycles.

As in the data, routine and abstract occupations are dominant occupations for low- and high-skilled individuals, respectively, and this does not change throughout their life-cycles. Among the low-skilled, a large number of individuals, especially those engaged in routine occupations, start to leave the labor force as early as in their 50s, well before they reach the social security eligibility age of 66. High-skilled individuals start to leave the labor force at a slower pace, and more than 20% of them remain in the labor force even at age 75 as shown in the data.



(a) Low-skilled



(b) High-skilled

Figure 12: Occupation over the Life-Cycle by Skills in the Initial Economy

Figure 13 shows average earnings by age and skills, normalized by average earnings of low-skilled individuals at age 25. Earnings rise steeply in their 20s and 30s as they accumulate human capital, and start to fall gradually in the late 40s and more sharply in the 50s and 60s, exhibiting a hump-shaped profile over the life-cycle. Figure 14 displays life-cycle profiles of assets. Individuals start with zero assets (by assumption) and accumulate wealth for both precautionary and retirement reasons. The profile peaks in the late 50s for the low-skilled and at around age 60 for the high-skilled and they decumulate assets as they age.

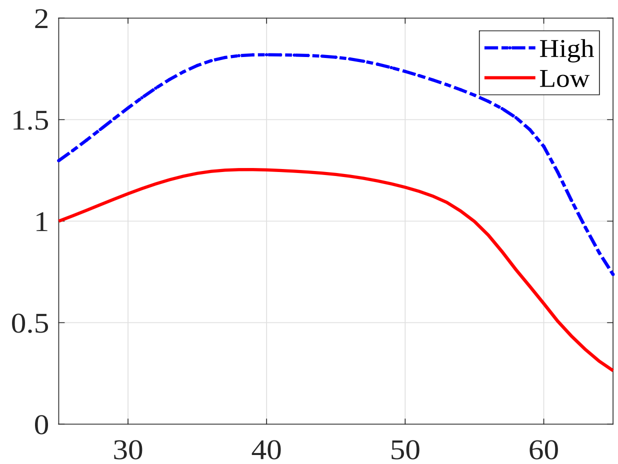


Figure 13: Earnings by Skills in the Initial Economy (Earnings of Low/25=1)

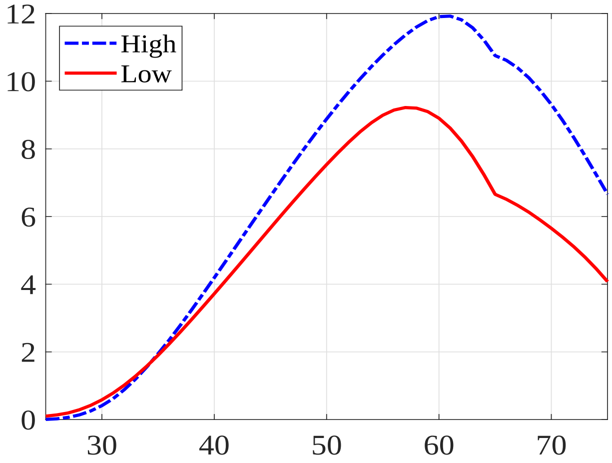


Figure 14: Assets by Skills in the Initial Economy (Earnings of Low/25=1)

5.2 Transition

In this section, we discuss computational results of the transition dynamics. The initial economy approximates the U.S. economy in 1980 and the transition begins that year when individuals learn the paths of occupation-specific wages.

We compute wages for the three occupations in 1983/85 (initial) and 2015/18 (final), as summarized in Table 2. The wages of routine occupations in the initial economy are normalized to one. We assume that wages change smoothly over a 30-year period from the initial economy and converge to the values in 2015/2018. After the wages converge to the final level, we assume that they will stay constant.

Table 2: Occupation-Specific Wages in the Transition

	Abstract	Routine	Manual
(1) Initial	1.06	1.00	0.60
(2) Final	1.15	0.92	0.62

In addition to the occupation-specific wages, we also change the assignment of initial occupations among entrants according to the CPS data for the period between the early 1980s (1983/85) to the late 2010s (2015/18). Table 3 shows the change in the distribution. We let them change smoothly over a 30-year period, in the same way as occupation-specific wages.[19]

[19]Obviously, an alternative simulation would be to feed in the exact paths of occupation-specific wages and initial occupation distribution as in the data. We chose to simulate smoothed paths of these variables because the focus of the paper is to quantify effects of the polarization trend and not cyclical fluctuations that occurred at the same time as polarization and various noises in the time series data.

Table 3: Initial Distribution of Occupations in the Transition

	Abstract	Routine	Manual	Total
Low				
(1) Initial	0.16	0.74	0.10	1.00
(2) Final	0.19	0.64	0.17	1.00
High				
(1) Initial	0.70	0.27	0.04	1.00
(2) Final	0.74	0.20	0.06	1.00

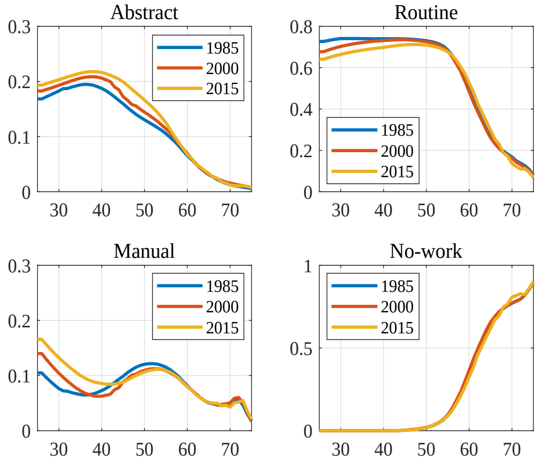
Figure 15 shows changes in the shares of occupations for each skill type. The data counterpart of the figure is Figure 7. Although there is a major shift in the shares from routine to abstract and manual occupations at the aggregate level data, such changes are not universally obvious once we express shares conditional on skill and age. For example, in Figure 7, there is no visible increase in the shares of abstract occupations, especially among the high-skilled who constitute the majority of the occupation. Our model generates a similar outcome among the high-skilled, despite a rapid increase in abstract wages, especially relative to wages of routine occupations, which continue to decrease.

Even after they learn about a more favorable wage path in abstract occupations, individuals do not switch occupations immediately, partly because of obstacles in moving across occupations captured by mobility costs in our model and also because of the loss of accumulated occupation-specific human capital and the need to reaccumulate human capital in a new occupation.

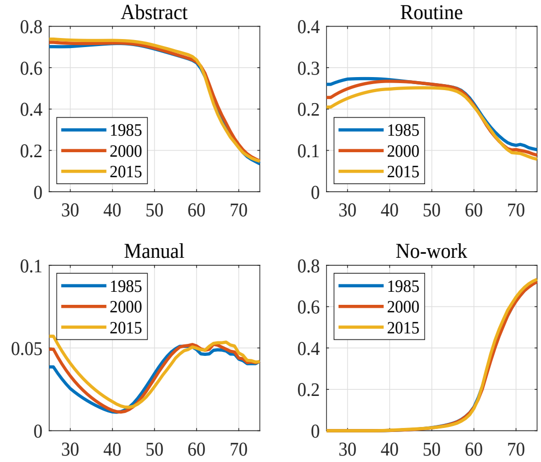
As shown in the upper right panels of Figure 15a and 15b, shares of routine occupations decline in the model for both low- and high-skilled individuals. The model also generates a rise in the shares of manual occupations for individuals in their 20s to early 40s as shown in the lower left panels, although we do not match well a rise in manual shares for individuals in their 40s and 50s among low-skilled individuals as seen in the CPS data.

There are other parts of the profiles in the transition that our model does not explain perfectly. For example, there is an increase in the shares of non-employment among both types of individuals and more noticeably among the low-skilled in the CPS data. Also, a decline in the routine share among the low-skilled is observed across a wider range of age groups in the data than in our model. Enriching the model with additional elements beyond factors associated with polarization are likely needed to fully explain the occupation trend observed in the past decades.[20] We leave the exploration for future research.

[20]For example, we conjecture that changes in provision of public insurance through social security and disability insurance systems that occurred during the past decades may help match a rise in non-participation, as explored, for instance, by Autor and Duggan (2003) and Kitao (2014).



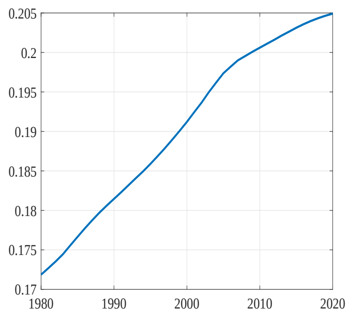
(a) Low-skilled



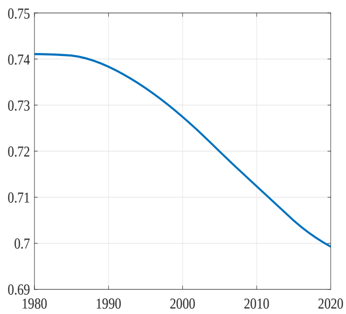
(b) High-skilled

Figure 15: Occupation by Age and Skills in Transition

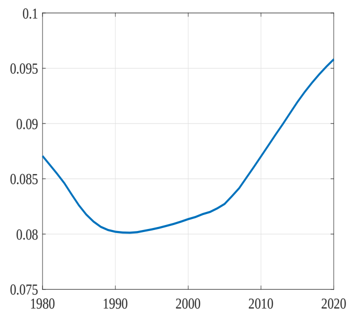
Figure 16 shows occupation shares for each skill type, averaged over individuals aged between 30 and 49, based on our model outcome. They show more clearly the overall trend of rising shares of abstract and manual occupations and a decline in routine shares for both skill types of workers, in line with the CPS data.



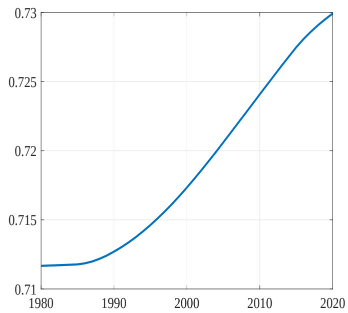
(a) Low/Abstract



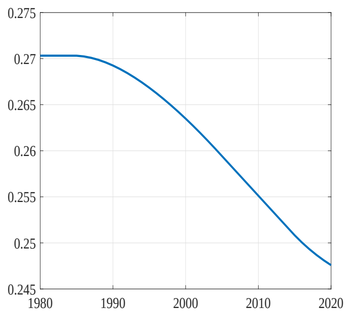
(b) Low/Routine



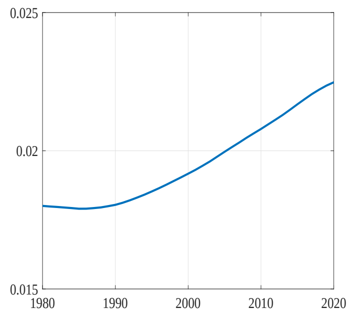
(c) Low/Manual



(d) High/Abstract



(e) High/Routine



(f) High/Manual

Figure 16: Occupation Shares in Transition (Workers aged 30/49)

Figure 17 shows average earnings for the three selected years during the transition.

While average earnings of high-skilled individuals rise monotonically, driven by a rise in abstract wages, earnings decline among low-skilled individuals. The path of skill premium, computed as a ratio of earnings of low- and high-skilled individuals, is shown in Figure 18, pointing to a rise in earnings inequality driven by polarization. Figure 19 shows the life-cycle profiles of assets in 1980 and 2015 and they indicate a rise in inequality in wealth across skill types.

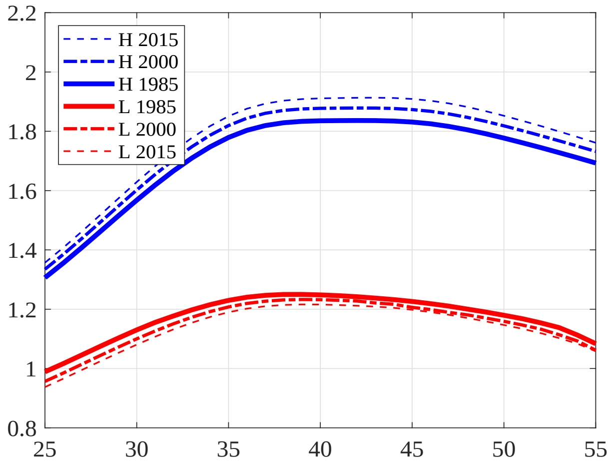


Figure 17: Earnings by Skills in Transition

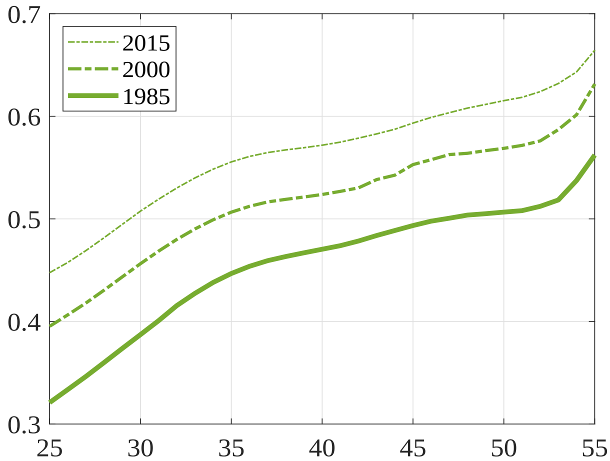


Figure 18: Skill Premium in Transition

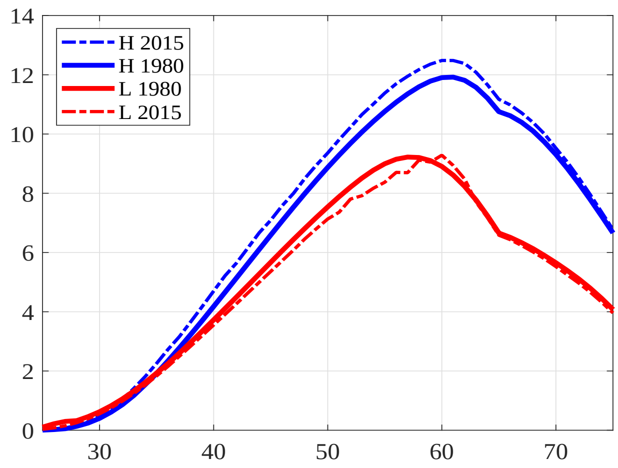


Figure 19: Assets by Skills in Transition

5.3 Welfare Analysis

We now turn our attention to welfare analysis of polarization. We quantify welfare effects by computing a consumption equivalent variation, denoted as CEV. More precisely, we ask each individual whether he would prefer to live in the status quo economy where there is no polarization or change in occupation-specific wages, or in an economy that goes through polarization. We quantify welfare effects by asking how much compensation, in terms of a percentage change in consumption levels across all possible states, he needs to receive in order for him to be indifferent to the status quo economy and the economy with polarization.[21]

Figure 20a shows CEV for individuals of different skills and ages in the initial economy and Figure 20b displays welfare effects for future generations, where each generation is indexed by the year of entry at age 25.

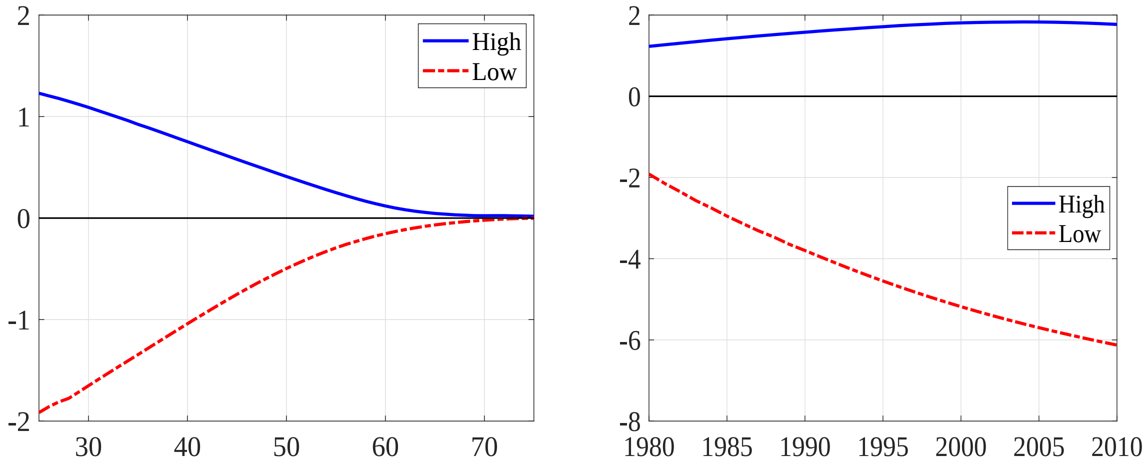
High-skilled and young individuals are the winners of polarization. The welfare gain of the high-skilled aged 25 in the initial economy is 1.2% in consumption equivalence, 0.8% for those aged 40 and 0.4% for age 50. The low-skilled experience a welfare loss and the larger the magnitude, the younger they are in the initial economy, and the welfare loss is nearly 2% in consumption equivalence for entrants in 1980.

As shown in Figure 20b, the gain of the high-skilled is larger for later generations as they would be able to fully enjoy rising abstract wages during their career. Symmetrically, the welfare loss of the low-skilled is larger for later cohorts and those entering the labor

[21] In other words, the welfare effect is computed as a proportional growth rate in consumption to keep the value of the value function unchanged from the status quo economy. Note that individuals in our model incur disutility from participation and from mobility across occupations. These costs are held unchanged at the levels under each of the two transition scenarios and only consumption levels are adjusted proportionally to quantify welfare effects.

market in 2010 would lose up to as much as 6% in consumption equivalence relative to an economy without polarization.

The low-skilled suffer from the path of routine wages that falls by 8% in the end, as well as from a change in the initial occupational distribution. As shown in Table 3, the share of routine occupations among low-skilled entrants falls by 10 percentage points from 74% to 64%, and large part of the decline is absorbed by an increase of manual occupations, whose share rises by 7 percentage points. Most of the welfare loss, however, is due to the shift in occupation-specific wages. To disentangle the two effects, we also compute welfare effects in an alternative economy, in which only occupation-specific wages change and initial occupation distribution is fixed at the level of the initial economy. Results are shown in Figure 21.[22] Welfare gains of the high-skilled are slightly higher and the welfare losses of the low-skilled are smaller than in the baseline polarization scenarios.



(a) By Age in 1980

(b) By Entry Year

Figure 20: Welfare Effects of Polarization (in CEV, %)

[22]Note that there is no change in welfare for those already in the labor force in 1980.

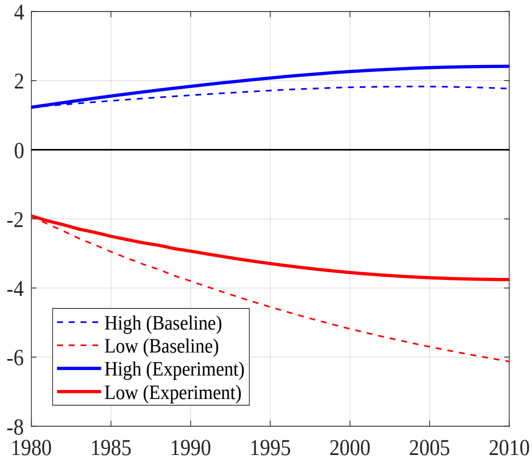


Figure 21: Welfare Effects of Polarization (in CEV, %): By Entry Year: Changes in Occupation-Specific Wages Only

Figure 22 shows the average welfare effect by cohort, computed as a population-weighted average of welfare effects across individuals of different skills. By just looking at these figures, one might conjecture that polarization brings welfare loss to the young and hurts also future generations. The figures, however, mask important heterogeneity in welfare effects across skills.

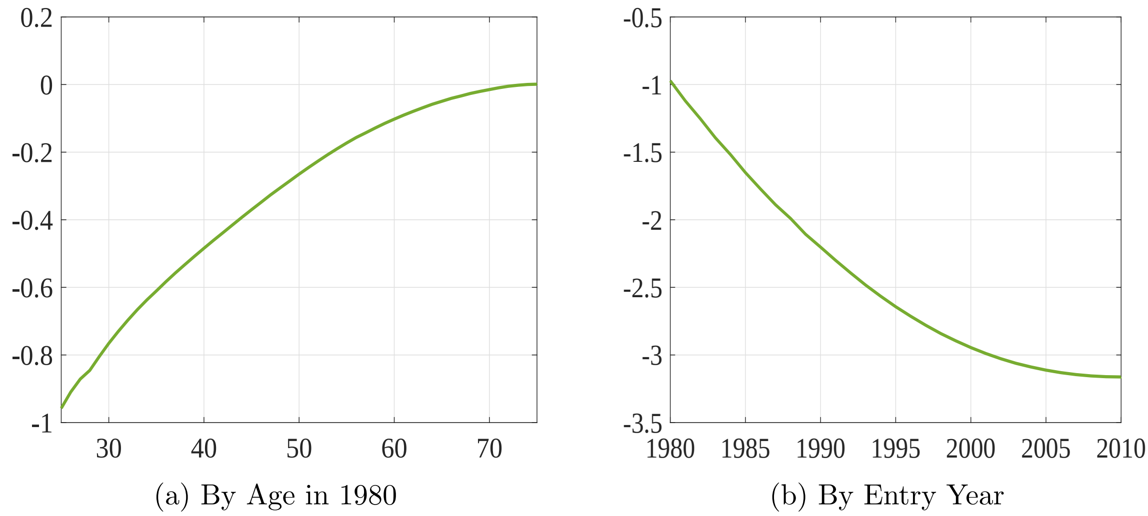
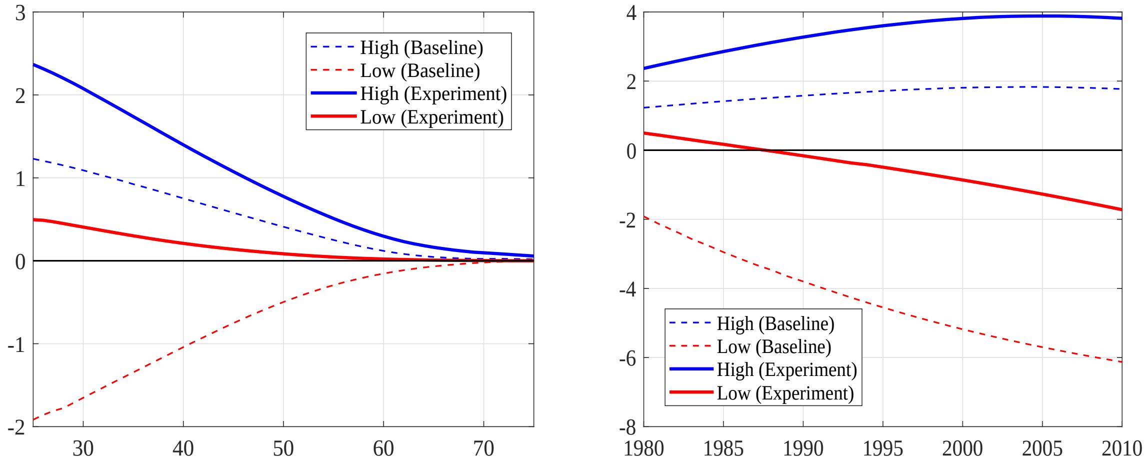


Figure 22: Welfare Effects of Polarization: By Cohort (in CEV, %)

Welfare Effects under Alternative Wage Scenarios: We run two additional experiments to understand the roles of a decline in routine wages and a rise in abstract wages. Figure 23 shows welfare effects of polarization in which routine wage is fixed at the level of the initial economy throughout the transition. The large welfare loss of low-skilled individuals of all ages in the initial economy is wiped away as shown in Figure 23a.

Future generations are also better off as shown in Figure 23b, although the welfare effects remain negative due to a shift in the initial distribution to manual occupations that remains under this experiment.

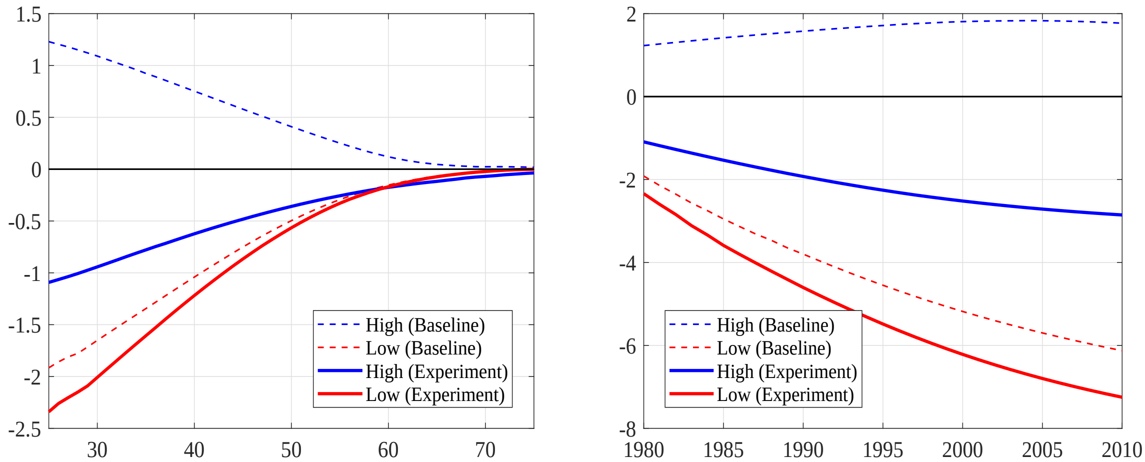


(a) By Age in 1980

(b) By Entry Year

Figure 23: Welfare Effects of Polarization: Without a Decline in Routine Wages (in CEV, %)

If abstract wages do not increase, welfare gains of high-skilled individuals disappear as shown in Figure 24. The welfare loss of the low-skilled will be larger but the quantitative effects, compared to a decline in the welfare of the high-skilled, are much smaller.



(a) By Age in 1980

(b) By Entry Year

Figure 24: Welfare Effects of Polarization: Without a Rise in Abstract Wages (in CEV, %)

6 Conclusion

This paper builds a full-blown life-cycle model populated by individuals of different occupations, skills, human capital, idiosyncratic labor productivity, and assets. It is used to account for occupational distribution and mobility over the life-cycle of heterogeneous individuals and to quantify welfare effects of polarization that occurred during the past decades and affected different groups of individuals. We show that high-skilled individuals gain from polarization while the low-skilled lose from it. Although everyone in the economy faces the same changes in occupation-specific wages and is able to move across occupations, mobility is restricted due to upward mobility costs that we calibrate to data as well as opportunity costs associated with occupation-specific human capital that individuals at different ages have already accumulated. The welfare gain is larger among younger high-skilled individuals as they can enjoy a continued rise in abstract wages throughout their careers. Similarly, the welfare loss of the low-skilled is larger among the younger and later generations.

The model can be extended in various dimensions to answer related questions. One natural question may be whether the trend of welfare effects across generations, which the model identifies, can be extrapolated for the future. It is an open question whether the high-skilled will continue to gain and polarization will continue, increasing inequality in income and wealth. We leave the question for ongoing future research.

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