Beyond Labor Market Polarization*

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Abstract

It is well documented that routine-biased technical change ("RBTC") led to labor market polarization during 1980-2000. In particular, the employment and wages of non-routine occupations, which include low-wage manual and high-wage cognitive ones, increased relative to routine occupations. I document that during 2000–2016, wage polarization stopped in that the wages of non-routine manual occupations fell in relative and absolute terms. I study the end of wage polarization through the lens of a dynamic general equilibrium model with RBTC, human capital accumulation, and occupational mobility. I find that during 2000–2016, RBTC continued to take place, but human capital accumulation and occupational mobility changed. In particular, compared to workers in routine occupations, workers in non-routine manual occupations had lower initial human capital and accumulated less human capital whereas workers in cognitive occupations had more initial human capital and accumulated more human capital than before. During 1980–2000 the changes in the human capital accumulation of the occupations were similar to those during 2000–2016, but during the second period mobility across occupations fell, which magnified the differences in human capital accumulation and led to the end of wage polarization.

Keywords: polarization, occupations, mobility, dynamic Roy model, human capital.

JEL Codes: E24, J24, J31, J62, O33.

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1 Introduction

The labor market in the United States showed a pattern of polarization during 1980–2000; wages and employment grew faster in high-wage and low-wage occupations, compared to the occupations in the middle of the wage distribution. This polarization of the labor market has been linked to the effect of routine-biased technical change ("RBTC").[1] Workers in middle-wage occupations, such as clerical and production workers, mostly perform routine tasks that can be easily understood and codified to be programmed and performed by machines. According to the RBTC hypothesis, the rapid computerization and automation of routine tasks during the last decades led to the displacement of workers in middle-wage occupations. At the same time, RBTC increased the demand for workers in low-wage occupations –e.g. bartenders, security guards– and high-wage occupations –e.g. managers, professionals–, who mostly perform non-routine manual and cognitive tasks that are more difficult to be codified and programmed to be performed by machines.

I document a new fact in the U.S. labor market during 2000–2016: wage polarization stopped, as the wage of low-wage occupations fell in absolute and relative terms, while employment polarization continued. This fact cannot be accounted for by RBTC alone, although there is ample evidence that it continued during this period.[2]

In this paper, I study why wage polarization ended during 2000–2016. I focus on the effect of changes in the pace of occupation-biased technical change –e.g. RBTC– and changes in occupation-specific human capital. I find that routine-biased technical change continued at a slightly lower pace during 2000–2016, and that it had a positive effect on the relative wage of low-wage occupations. In contrast, human capital accumulation and occupational mobility changed during 2000–2016 and led to the end of wage polarization. In particular, compared to workers in routine occupations, I identify that workers in low-wage occupations accumulated less human capital and that young workers had lower human capital than before. The increase in the relative wage of high-wage occupations was due to an increase in the human capital of young workers in these occupations and due to high human capital accumulation. During 1980–2000, I find similar changes in the human capital accumulation of the occupations, but during 2000–2016 these changes were amplified by a fall in occupational mobility.

[1]See for example, Autor, Levy and Murane (2003), Autor, Katz and Kearney (2006), Autor and Dorn (2013).

[2]See for example, Hershbein and Kahn (2018), Eden and Gaggl (2018), and Bharadwaj and Dvorkin (2019).

These results have important implications for the increasing wage inequality in the U.S.. The polarization of wages during 1980–2000 increased inequality in the upper half of the wage distribution –as measured by the 90/50 wage percentile ratio– but it decreased inequality in the lower half of the wage distribution –as measured by the 50/10 wage percentile ratio–.[3] On the contrary, the decrease in the relative wage of low-wage occupations during 2000–2016 also increased inequality in the lower half of the wage distribution. Thus, my results imply that the changes in the accumulation of occupational human capital and lower occupational mobility contributed to the increase in wage inequality during 2000–2016. This is reinforced by the ongoing polarization of employment that, through the increase in the employment shares in the extremes of the wage distribution, increases the dispersion of human capital and, as a result, of wages. Moreover, the increasing share of young workers with relatively lower human capital in low-wage occupations seems to be a secular trend in the U.S. labor market, that I identify since 1980. If this trend continues and mobility across occupations remains low, inequality is likely to increase further, as workers with low human capital stay longer periods in low-wage occupations with low human capital accumulation.

I start by documenting three motivating facts related to the level of occupational human capital. First, young workers, who tend to have low human capital, increasingly work in low-wage occupations. The share of workers aged 16–24 in these occupations increased from 10.5% in 1980 to 23.6% in 2016. Second, workers in low-wage occupations accumulate less human capital, as compared to those in other occupations. Third, the mobility of workers across occupations decreased after 2000.

To quantify the importance of technical change and changes in occupation-specific human capital for the onset and the end of wage polarization, I develop a general equilibrium model that features: (i) occupation-biased technical change, (ii) human capital accumulation, and (iii) occupational mobility. In the model, output is produced combining the labor services of low-wage (manual), middle-wage (cognitive) and high-wage (routine) occupations. Occupation-biased technical change affects the productivity of the labor services of each occupation.

The labor supply side of the model builds on the dynamic Roy model developed by Dvorkin and Monge-Naranjo (2019), where the comparative advantage of workers is determined by their current occupation and occupation-specific idiosyncratic productivity shocks. Workers have stochastic lifetimes, maximize their expected lifetime utility and can switch occupations in any period, but when

[3] See Autor, Katz and Kearney (2006).

they do they can only transfer part of their human capital. Occupational mobility arises because workers draw relatively high productivity shocks for other occupations that compensate the loss of transferred human capital. The model takes into account the heterogeneity in the accumulation of human capital in different occupations and features cohorts of young workers who self-select according to their comparative advantage.

The quantitative strategy consists in comparing three equilibria of the model, meant to represent the U.S. economy in 1980, 2000 and 2016. The three equilibria differ exogenously in the level of occupation-biased technical change, the occupation-specific productivity shocks, the transferability of human capital, and the human capital of young workers. Given these exogenous factors, the model endogenously determines the distribution of employment and human capital across occupations, which together with the equilibrium wages per unit of human capital determine occupational wages.

The decrease in the relative human capital of young workers in low-wage occupations was driven by a lower comparative advantage of the increasing number of workers who join these occupations. On the contrary, the increase in the human capital of young workers in high-wage occupations was due to relatively higher human capital of the workers that sort into these occupations. In line with this finding, during 1980–2016 there was a strong increase in the share of young workers in high-wage occupations with a college degree –from 29.0% in 1980 to 53.0% in 2016–. The lower accumulation of human capital in low-wage occupations is consistent with workers performing mostly manual tasks –e.g. mopping, serving food, preparing cocktails– that can be quickly mastered and hardly provide opportunities to learn and accumulate human capital over time, whereas the higher accumulation in high-wage occupations is consistent with workers performing mostly cognitive tasks –e.g. programming, presenting, analyzing data– that take time to master and provide many opportunities to learn. Lower occupational mobility decreased human capital accumulation during 2000–2016 in low-wage occupations because a higher share of workers stayed longer periods in these occupations accumulating relatively less human capital and because a lower share of workers with relatively high human capital transitioned from middle-wage and high-wage occupations. Because workers in high-wage occupations accumulate relatively more human capital, the fall in occupational mobility had a positive effect on their human capital accumulation.

I also conduct counterfactual experiments in which I isolate the effect of each of the forces in the model on the employment shares and wages of the occupations. I show that RBTC was the main driver of the polarization of employment in 1980–2016 but it does not generate the changes in average occupational wages during this period. This stresses the importance of changes in human capital accumulation and occupational mobility to understand the changes of occupational wages over time. In the absence of these changes, the positive effect of RBTC on the relative wages per unit of human capital of low-wage and high-wage occupations attracts workers with lower comparative advantage and decreases their relative average human capital.

Related Literature. There is a limited number of studies, closely related to this paper, that consider the role of occupational mobility and occupation-specific human capital to analyze the polarization of the labor market. This paper builds on the dynamic Roy model developed by Dvorkin and Monge-Naranjo (2019), who study the effect of automation and task-biased technological change on growth and earnings inequality in the U.S.. In this paper, I embed this framework in a tractable production structure and I focus on the mechanisms that explain the end of wage polarization. Another difference is that I allow for exogenous changes in the parameters that affect occupational mobility and the sorting of young workers, that prove to be important to explain the changes in occupational wages. Kitao and Kikuchi (2020) study the welfare effects of polarization with a partial equilibrium overlapping generations model in which workers save, choose their occupation and accumulate human capital over their life-cycles. In this paper, I focus on the general equilibrium effects of occupation-biased technical change on the accumulation of human capital and the mobility of workers.

This paper contributes to the vast literature that studies the polarization of the U.S. labor market. I document the empirical evidence on the changes in occupational employment shares and wages using the same methodology and data sources than most authors in this literature, following the seminal contributions of Autor, Katz and Kearney (2006) and Acemoglu and Autor (2011).[4] My contribution is extending this analysis to 2016 and documenting a set of new facts related to the changes in the sorting patterns of young workers, wage growth with age, and occupational mobility during 1980–2016. Cortes (2016) uses the PSID to document occupational mobility during 1976–2007 for the same three broad occupational groups that I consider but he focuses on the selection of workers in middle-wage occupations according to their estimated ability. Cortes et al. (2014) use

[4] See also Autor and Dorn (2013), Autor (2015), Cerina, Moro and Rendall (2016), Bárány and Siegel (2018),

CPS data to study the disappearance of routine jobs by analyzing flows from and to unemployment and non-participation in the labor market.

Several authors in the polarization literature also consider the importance of self-selection of workers into low-wage, middle-wage and high-wage occupations based on their comparative advantage. Related to this paper, Autor (2013) analyze the growth of low-wage occupations and the polarization of the labor market through the lens of a spatial equilibrium model. In their model, labor services for low- and middle-wage occupations are provided by low-skill workers who are heterogeneous in their ability for performing routine tasks. They focus on the interaction of consumer preferences for variety and lower costs of computer capital for automating routine tasks as the drivers of the polarization of the labor market. Cortes, Jaimovich and Siu (2017) incorporate a decision of non-participation in the labor market to this model. The main difference with these papers is that I incorporate the accumulation of occupation-specific human capital and the mobility of workers across occupations, which I show are key margins for understanding the polarization of the labor market. I abstract from considering physical capital and consumer preferences because I am interested in analyzing the onset and end of wage polarization, rather than identifying the sources of occupation-biased technical change. The effect of these forces on employment and wages are captured in my model through changes in the parameters that measure occupation-biased technical change.

Finally, this paper relates to the literature that studies the importance of the human capital specific to occupations and occupational mobility to determine labor market outcomes. Closely related to this paper, Kambourov and Manovskii (2009) and Sullivan (2010) show that occupation specific human capital is a key determinant of wages. Recently, Cubas and Silos (2020) show that insurance from progressive taxation encourages mobility and leads to better matches of workers to occupations. Also, Poletaev and Robinson (2008), Gathmann and Schönberg (2010) and Yamaguchi (2012) have related this human capital to the tasks that workers perform in their occupations, which differentiate the three main occupational groups of the polarization literature.

The rest of this paper is organized as follows. Section 2 discusses the main data sources and illustrates the empirical evidence on the polarization of the U.S. labor market, human capital accumulation and occupational mobility. Then, Section 3 presents the model motivated by the empirical evidence. Next, Section 4 discusses the parametrization, and Section 5 provides the main results. Section 6 presents the counterfactuals and Section 7 concludes.

2 Evidence on Polarization and Occupational Mobility

2.1 Data Sources

I follow the authors in the polarization literature[5] and analyze the changes in occupational employment and wages using the nationally representative 5% samples of the Census and American Community Survey (ACS) from IPUMS.[6] I consider the Census 1980[7] and 2000, and extend the analysis of the polarization in the U.S. labor market by including the 2014-2018 5-year ACS –which I refer to as the 2016 sample–. I document the changes over the period 2000–2016 and compare these to those occurred during 1980–2000.

I measure occupational mobility using the Panel Study of Income Dynamics (PSID), a longitudinal household survey representative of the US economy, conducted annually between 1968 and 1997 and biennially afterwards. Because of its panel structure the PSID has been widely used to measure yearly occupational mobility.[8] I consider the core PSID sample (SRC) and exclude the immigration sample, the Latino sample and the oversample of low-income households. To make the analysis comparable before and after 1997, I calculate occupational mobility as the fraction of workers who report a change in their occupational code between t and $t+2$ and then report the implied yearly occupational mobility.[9] I measure occupational mobility in six-year periods starting in each odd year –e.g. 1979–1985, 1971–1977– to make the selection comparable before and after 1997 and to ensure that the number of observations in each period is sufficient to properly measure mobility from and to all the occupations considered.[10]

[5]See for example, Autor, Katz and Kearney (2006), Acemoglu and Autor (2011) and Autor and Dorn (2013).

[6]Available at `https://usa.ipums.org/usa/`.

[7]Most authors analyze polarization since 1980 but Bárány and Siegel (2018) with a similar approach find evidence of it since the 1950s.

[8]See for example, Kambourov and Manovskii (2008), Cortes (2016) and Cubas and Silos (2020). The CPS has also been used to measure occupational mobility –e.g. Moscarini and Thomsson (2007), Moscarini and Vella (2008) and Xu (2019)– but because of its sampling design we can only measure mobility over shorter periods than a year. Also, before 1994 the coding of occupations was independent of the occupations reported in previous months, which led to significant noise. The main disadvantages of the PSID are that its core sample excludes immigrants arriving in the US after 1968 and that the coding of occupations was reviewed to ensure its reliability only until 1980. For an in-depth discussion of the advantages and disadvantages of the PSID and the CPS to measure occupational mobility see Kambourov and Manovskii (2013).

[9]If the matrix $\boldsymbol{\mu}^{\mathbf{2}}$ represents the two-year transitions across occupations (μ_{jk}^{2y}), $\boldsymbol{\mu} = (\boldsymbol{\mu}^{\mathbf{2}})^{\mathbf{1/2}}$ represent the yearly transitions.

[10]Each six-year period contains between 4,716 and 8,026 observations. Mobility cannot be calculated from 1999 to

I focus on (i) 16-64 years-old, (ii) working for a wage or salary –not self-employed–, (iii) working full-time and full-year –35+ hours per day and 50+ weeks per year–, (iv) earning at least half the Federal minimum wage, (v) not working in the military, farming, forestry or fishing occupations.[11] To measure occupational mobility in the PSID samples I consider workers with only one job.[12] Additionally, I restrict the PSID sample to heads of households because they are the only household members for whom there is detailed information on labor market outcomes for the whole period of analysis.[13] Unless otherwise noticed, all observations from the Census and ACS samples are weighted using the person weights and from the PSID using the cross-section person weights. All dollar amounts are inflated to 2016 using the Personal Consumption Expenditure (PCE) index.[14]

I classify occupations into the three broad groups commonly used in the polarization literature:[15]

- **High-wage:** managerial, professional, technical.
- **Middle-wage:** administrative support and sales, mechanics and repairers, construction trades, extractive, precision production, machine operators, assemblers and inspectors, transportation and material moving.
- **Low-wage:** housekeeping and cleaning, protective services, other services.

These occupational groups are key to the analysis of the polarization of the labor market because the main tasks that workers perform in each of these groups are differently affected by RBTC. Acemoglu and Autor (2011) show that workers in **middle-wage** occupations mostly perform **routine** tasks, which are more likely to be substituted by machines, whereas workers in **high-wage** occupations mostly perform **non-routine cognitive** tasks and workers in **low-wage** occupations perform **non-routine manual** tasks, which are less likely to be substituted by machines. Technical change and the rapid decline in the cost of computers and machines during the last decades led

2001 because in the latter PSID changed the classification of occupations from the Census 1970 to the Census 2000, which is not entirely comparable to the former.

[11] This is a common restriction in the polarization literature as these occupations represent only around two percent of employment since 1980 (Autor, 2015).

[12] In the Census and ACS samples workers report the occupation in which they worked the most hours during the previous year and it is not possible to distinguish those with more than one occupation.

[13] I include men and women because there is strong evidence that during this period there have been important gender differences that shaped the polarization of the US labor market. See for example, Cerina, Moro and Rendall (2016) and Cortes, Jaimovich and Siu (2018).

[14] Appendix A includes further details on the construction of each sample and descriptions of the variables of interest.

[15] See for example, Acemoglu and Autor (2011), Autor and Dorn (2013), and Cortes (2016).

to the computerization and automation of routine tasks as, in words of Autor, Levy and Murane (2003), "these tasks require methodical repetition of an unwavering procedure, they can be exhaustively specified with programmed instructions and performed by machines." According to the RBTC hypothesis, machines and computers displaced workers in middle-wage occupations, who used to perform those routine tasks, and increased the demand of workers in low- and high-wage occupations, who mostly perform tasks that are more difficult to codify and programmed to be performed by machines.[16]

I map the occupations from the classification schemes of each survey to the three broad groups by using 302 detailed occupations that cover all non-farm and non-military employment in the U.S.. These occupations –an extension of the *occ1990dd* occupational scheme developed by Autor and Dorn (2009), to make them consistent up to the classification used in the 2018 American Community Survey (ACS)– have the advantage of being comparable over time, such that the appearance and disappearance of more disaggregated occupations happens within these 302 occupations.

2.2 Evidence on Polarization, Human Capital and Occupational Mobility

Figure 1 shows the graphs most commonly used in the literature to document the polarization of the U.S. labor market from 1980 to the early 2000s.[17] Panel 1b shows smoothed changes in employment shares and Panel 1a shows smoothed changes in log-hourly wages during 1980–2000 and 2000–2016 for the 302 detailed occupations, ranked on the x-axis by their average wage in 1980.

Panel 1a shows a new fact: during 2000–2016 wage polarization stopped as the wage growth was flat for the lowest forty percent of occupations –at around one percent– and increased monotonically thereafter.[18] This contrasts with the pattern of wage polarization –higher wage growth in both extremes of the wage distribution– previously documented during 1980–2000. The growth of log-hourly wages was lower for all percentiles of the wage distribution in the latter period, as it includes the negative effects of the Great Recession of 2007–2009, but the difference in wage growth with respect to 1980–2000 increases as we move from the 50th to the lowest percentile. Panel 1b shows that employment polarization occurred during both periods, but during 1980–2000 employment

[16] For a full description of the "routinization hypothesis" see Autor, Levy and Murane (2003) and Autor (2013).

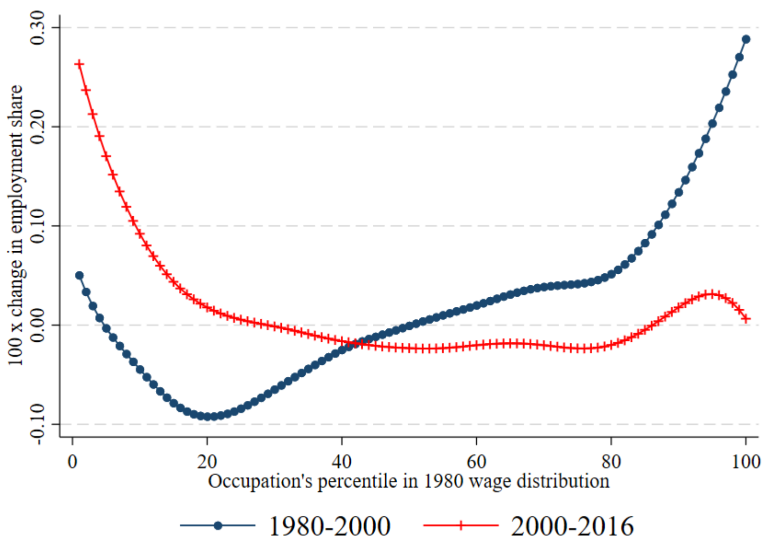
[17] See for example, Autor, Katz and Kearney (2006), Autor and Dorn (2009) Acemoglu and Autor (2011), Firpo, Fortin and Lemieux (2011),Autor and Dorn (2013), and Bárány and Siegel (2018).

[18] Autor (2015) and Mishel, Shierholz and Schmitt (2013) previously documented a similar pattern for the period 2000–2007.

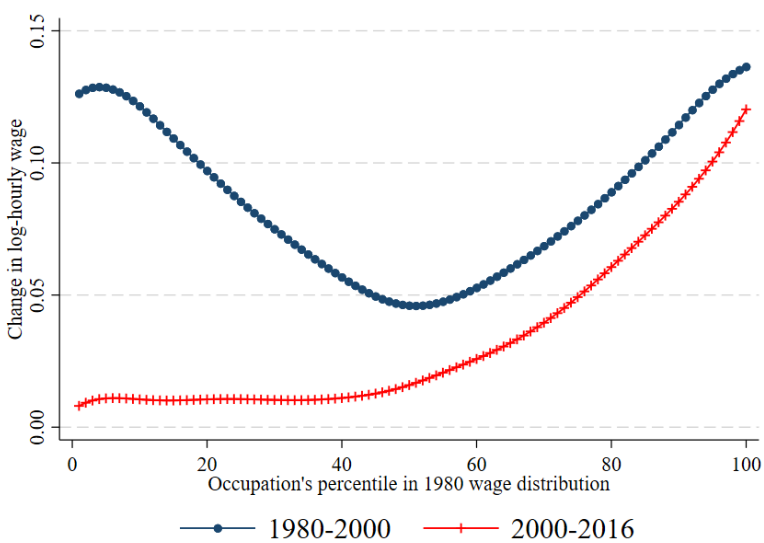
gains were relatively higher for the top twenty percent, while during 2000–2016 employment gains were relatively higher for the lowest twenty percent and modest for the highest twenty percent.

Figure 1: Smoothed Changes in Employment and Hourly Wages
Periods 1980–2000 and 2000–2016

(a) Smoothed Changes in Employment Shares by Occupational Average Wage in 1980



(b) Smoothed Changes in Hourly-wage by Occupational Average Wage in 1980



Notes: the figure shows the changes in employment shares and log-hourly wages using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations). On the x-axis the 302 detailed occupations are ranked by their average wage in 1980. All workers are weighted by the product of their weeks worked, hours worked and Census weight.

Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

The changes in wages by the percentile of occupations in the 1980 wage distribution –documented in Figure 1– reduced the wage of low-wage occupations relative to that of middle-wage, as defined in Section 2.1.[19] In Table 1, I show that during 2000–2016 the wage of low-wage occupations fell 2.3% more than that of middle-wage occupations, which erased the gains from 1980–2000 and led to a lower hourly wage relative to middle-wage occupations than in 1980 –0.761 vs. 0.766–. In line with Figure 1, the wage of high-wage increased during both periods and the hourly wage relative to that of middle-wage occupations went from 1.38 in 1980 to 1.71 in 2016. The polarization of employment in terms of the three broad occupational groups was similar during both periods, with a relatively higher increase in the employment of low-wage occupations during 2000-2016, when wage polarization stopped. It is important to note that Figure 1 and Table 1 convey different information but reveal similar patterns in the changes of wage and employment polarization. Specifically, Figure 1 shows locally weighted smoothing regressions –bandwidth of 0.8 with 100 observations–, at each percentile of the wage distribution using the 302 detailed occupations, whereas in Table 1 I aggregate these occupations into the three occupational groups defined in Section 2.1 and calculate average log-hourly ages and employment shares. This explains why, for example, the changes of log-hourly wages in Figure 1 are above zero at all percentiles but when we consider the occupational groups in Table 1 the average log-hourly wages fall for low- and middle-wage occupations.

In Appendix A.3, I show that the decrease of the average wage in low-wage and that the increase of the average wage in high-wage during 2000–2016, relative to middle-wage, are not driven by the choice of the end year selected after 2000 or by the Great Recession. In Figure 14, I plot the average relative wage of low- and high occupations in the Census 1980, 1990, 2000, and in the yearly samples of the American Community Survey during 2005–2018, published by IPUMS.[20] Panel 14a of this figure shows that the average wage of high-wage occupations, relative to that of middle-wage, during 2005–2018 is consistently higher than that in all Census samples, with a maximum of 1.725 in 2018 and a minimum of 1.656 in 2005. Panel 14b shows that the relative wage of low-wage occupations was below its in 2000 during 2005–2018 –and generally below the value in 1990–, ranging from 0.755 in 2016 to 0.777 in 2010.

The end of wage polarization during 2000–2016 could be the result of changes in the process of

[19] In Appendix A.3 I show that the facts from Table 1 hold if I also consider non-full-time and non-full-year workers.
[20] I exclude the years 2000–2004 because not all the variables required to select my sample are available.

Table 1: Employment Shares and Log-hourly Wages by Broad Occupational Group. Years 1980, 2000 and 2016

	Employment share			Log-hourly wage		
	Level	Δ		Level	Δ	
	1980	80-00	00-16	1980	80-00	00-16
High-wage	28.1%	6.6%	5.9%	3.13	16.4%	8.7%
Middle-wage	62.6%	-8.6%	-8.4%	2.84	4.2%	-0.4%
Low-wage	9.3%	2.0%	2.5%	2.56	7.5%	-2.7%

Notes: the table shows employment shares and log-hourly wages in 1980 and changes in employment shares, in the left panel, and log-hourly wages, in the right panel, for low-wage, middle-wage and high-wage occupations during 1980–2000 and 2000–2016.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

RBTC but this hypothesis is not consistent with the ongoing employment polarization nor with the ample evidence available that RBTC continued during this period. Bharadwaj and Dvorkin (2019) show that according to the International Federation of Robotics (IFR) the number of robots per thousand workers in the U.S. more than doubled between 2000 and 2017. Eden and Gaggl (2018) using data from the Bureau of Economic Analysis (BEA) show that the share of information and communication technologies (ICT) –an important driver of the automation of routine tasks–[21] in total capital also more than doubled between 2000 and 2014. Hershbein and Kahn (2018) find that in job postings skill requirements related to non-routine tasks increased in MSAs that were hit harder by the Great Recession and that these were correlated with increases in capital investments.

This evidence suggests that there must be an important force other than RBTC that explains the end of wage polarization. I argue that changes in occupation-specific human capital are key to understand the end of wage polarization as this is an important determinant of labor market outcomes, particularly wages.[22] Moreover, several authors have shown that occupation-specific

[21] See for example, Michaels, Natraj and Reenen (2014) and Böckerman, Laaksonen and Vainiomäki (2019).

[22] For example, Kambourov and Manovskii (2009) show that five years of occupational tenure are associated with an increase in wages of 12% to 20% and that these returns are significantly more important than returns to employer or industry tenure. In line with these findings, Sullivan (2010) finds that in several occupations occupation-specific

human capital is intimately related to the tasks that workers perform in their occupations[23] and the three broad occupational groups, key for understanding the polarization of the labor market, are characterized by different type of tasks. In the remainder of this section I show some motivating facts related to the level of human capital of these three occupational groups.

In the panels of Figure 2, I plot the share of employment of each of the three broad occupational groups for ten different age intervals. The main takeaways from this figure are: (i) young workers –16–24 years old– increasingly sort into low-wages occupations, (ii) older workers –particularly prime-aged, 25–54 years old– increasingly sort into high-wage occupations, and (iii) the decrease in the share of middle-wage occupations is more homogeneous across age groups. These trends resulted in low-wage occupations employing younger workers over time, relative to high- and middle-wage occupations. Specifically, while in 1980 workers in low-wage were 0.2 and 1.2 years older than those in high- and middle-wage occupations, respectively, in 2016 they were 2.7 and 1.9 years younger.[24] These changes in the age composition of the three occupational groups tend to decrease the relative wage of workers in low-wage occupations as younger workers have lower wages, partly due to lower levels of human capital (Ben-Porath, 1967).

Wages tend to increase with age as workers accumulate human capital through education, experience and training (Becker, 1994; Mincer, 1994). To provide evidence on the differences in human capital accumulation, for each occupational group I estimate the following regression on log-hourly wages in 1980, 2000 and 2016:

$$\log(w_{it}^j) = \alpha_t^j + \beta_{1t}^j age + \beta_{2t}^j age^2 + \boldsymbol{X}\boldsymbol{\gamma}_t^j + \epsilon_{it}^j \tag{1}$$

where i = individual, j = occupation, t = year. $\boldsymbol{X}$ includes dummies for non-white, female, some college and completed college education.

On Figure 3, I show the estimated quadratic returns to age ($\beta_{1t}^j age + \beta_{2t}^j age^2$) relative to workers who are sixteen year-old in each occupation and year. This Figure shows that at each point in time

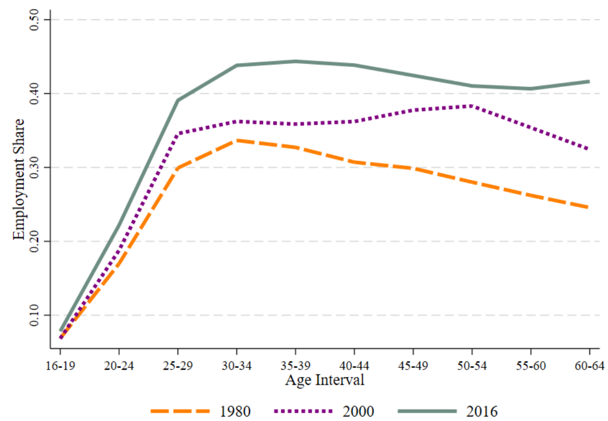
human capital is the most important determinant of wages, experiencing an increase of 14% in their wages after five years of occupation specific experience.

[23] See for example, Poletaev and Robinson (2008), Gathmann and Schönberg (2010) and Yamaguchi (2012).

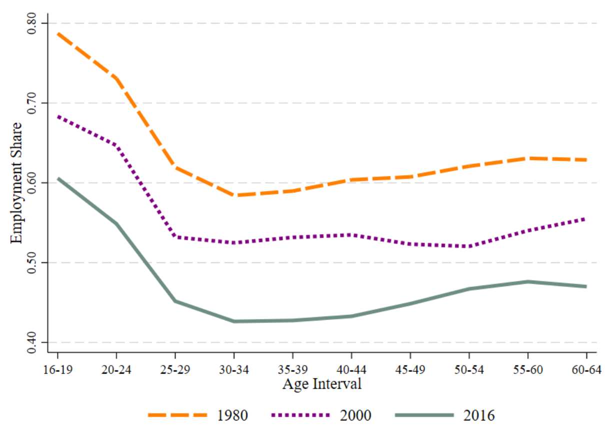
[24] In Appendix A.4 I show that the cumulative density function (CDF) by age for low-wage occupations increasingly accumulates more mass for younger ages. These findings are in line with those of Autor and Dorn (2009) for the period 1980–2005 and with those documented by Cortes et al. (2014) during 1976–2012 using data from the Current Population Survey (CPS).

Figure 2: Employment Shares Over the Life-cycle by Broad Occupational Group. Years 1980, 2000 and 2016

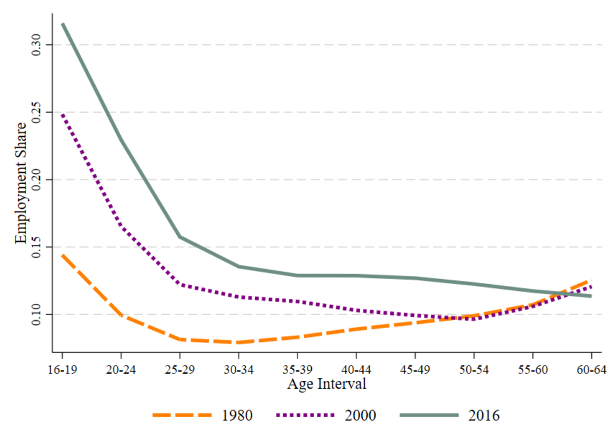
(a) High-wage



(b) Middle-wage



(c) Low-wage



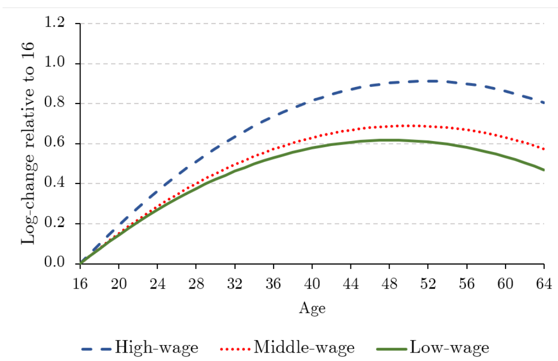
Notes: the figure shows the shares of employment for low-, middle- and high-wage occupations in 1980, 2000 and 2016 for workers in ten age intervals.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

the wage of low-wage occupations grows the least and that of high-wage occupations grows the most with age. This suggests that human capital accumulation in low-wage occupations is lower than in high- and middle-wage occupations throughout the whole period. In 2000, the difference between the estimated returns in low- and middle-wage was lower but in 2016 this difference increased and was even higher than in 1980. If middle-wage occupations were negatively affected by RBTC during 2000–2016 but their wages grew relatively faster with age compared to the period 1980–2000, the changes in human capital accumulation must have favored these occupations.

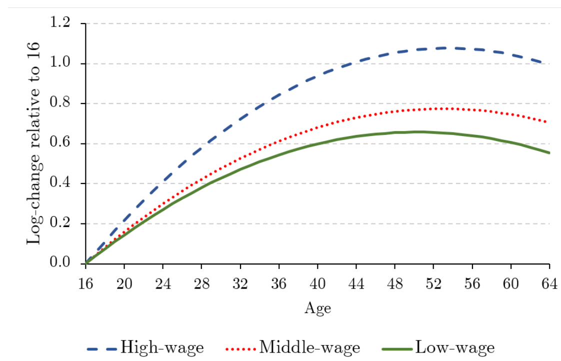
Figure 3: Estimated Returns to Age by Broad Occupational Group. Years 1980, 2000 and 2016

(a) High-wage

(b) Middle-wage



(c) Low-wage

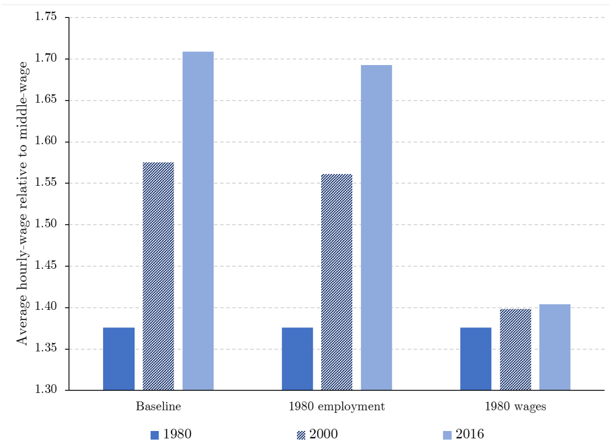


Notes: the figure shows the estimated log-returns to age, $\beta^j_{1t}age + \beta^j_{2t}age^2$ from Equation 1, for low-, middle-, and high-wage occupations in 1980, 2000, and 2016. These returns are relative to 16-year old workers in each occupation. *Source:* Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

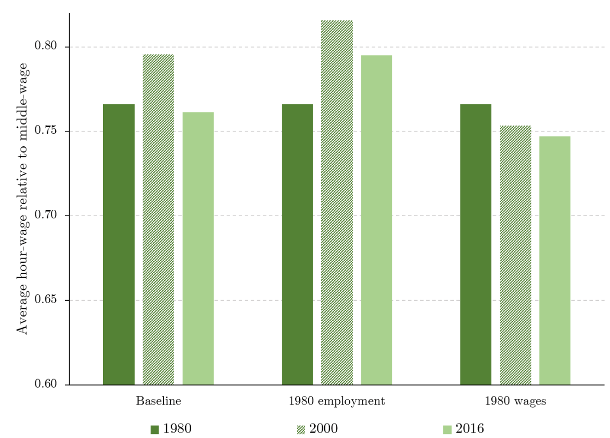
Figure 4 summarizes the effect of the forces described in Figure 2 and Figure 3 on the evolution of the wages of the three broad occupational groups during 1980–2016. In this Figure, I compare the average hourly-wages of high-wage and low-wage occupations, relative to middle-wage, in 1980, 2000 and 2016 to two counterfactuals. In the first counterfactual, I fix the distribution of employment by age within each broad occupational group to that in 1980 and let wages change for each age-occupation combination, while in the second counterfactual I fix wages by age and occupation at its 1980 levels and let the employment shares change. For high-wage occupations, both the changes in employment and wages by age increased the relative wages of their workers, but the latter explains almost all the variation. In line with the evidence in Figure 2, Panel 4b shows that the increasing share of young workers in low-wage occupations during 1980–2016 decreased their relative wage significantly. The changes in wages by age had a positive effect on the relative wage of these occupations during 1980–2000 and a negative effect during 2000–2016. This reinforces the hypothesis that if RBTC continued during the second period, the changes in human capital accumulation must have driven the relative wage of low-wage occupations downwards.

Figure 4: Counterfactual Wages. Fixed Employment Shares and Wages by Age and Broad Occupational Group. Years 1980, 2000 and 2016

(a) High-wage



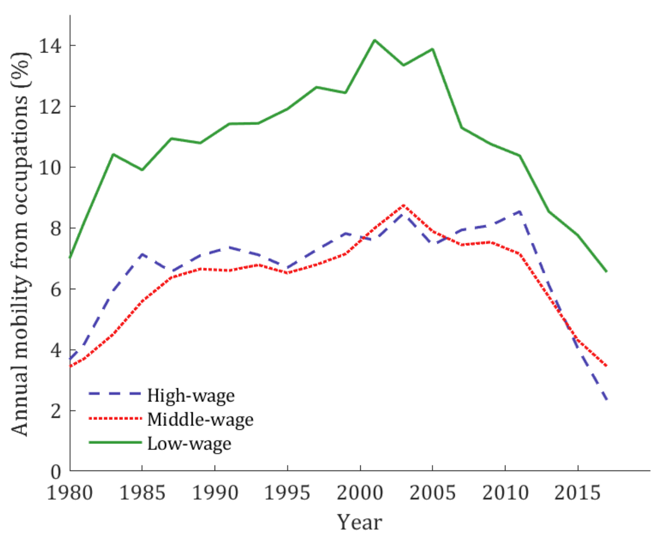
(b) Low-wage



Notes: the figure compares the average hourly-wages of high- and low-wage occupations, relative to middle-wage, in 1980, 2000 and 2016 to two counterfactuals. In the first counterfactual, I fix the employment shares by age within each broad occupational group at its 1980 levels and let wages change for each age-occupation combination, whereas in the second counterfactual I fix wages by age and occupations at the 1980 levels and let the employment shares change.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

Figure 5 shows that mobility from the three broad occupational groups followed a common trend over time: increases during the 1980s and 1990s and falls sharply after 2000, coinciding with the end of wage polarization. The trend for the first two decades is a well-known fact documented by Kambourov and Manovskii (2008), while the decrease after 2000 was documented by Moscarini and Thomsson (2007), Moscarini and Vella (2008), and Xu (2019) using CPS data but, to the best of my knowledge, this is the first time that it is documented using the PSID. In Appendix A.5 I decompose the mobility around 1980, 2000 and 2016[25] and show that these changes hold for moves from and to all occupations. In a context in which human capital is occupation-specific, changes in mobility affect the flow of human capital across occupations and this has an effect in wages.[26] The decrease in mobility during 2000–2016 implied that the share of workers in low-wage occupations coming from high- and middle-wage each year decreased from 10.5% around 2000 to 4.0% around 2016. If, as the evidence suggests, these workers had relatively high human capital compared to those that stay in low-wage occupations, the decrease in occupational mobility would decrease the relative wage of workers in low-wage. Also, lower mobility means that workers stay longer periods in one occupation, which hurts the accumulation of human capital in occupations like low-wage, where workers seem to have relatively lower human capital growth.

Figure 5: Annual Mobility From Occupations. Six-year Rolling Averages. Period 1975–2017



Notes: the figure shows annual mobility from each of the three broad occupational groups over six-year periods finishing in each of the odd years from 1975 to 2017. To make the analysis comparable before and after 1997 –when the PSID started to conduct biennial surveys– I calculate occupational mobility as the fraction of workers who report a change in their occupational code between t and $t+2$ and then calculate the implied yearly occupational mobility. *Source:* Panel Study of Income Dynamics.

[25] I consider 1973–1979 for 1980, 1993–1999 for 2000 and 2011–2017 for 2017.

[26] For example, Kambourov and Manovskii (2009) show that the increase in mobility between the 1970s and the 1990s can account for a high fraction of the increase in wage inequality.

To sum up, in this Section I have established that the polarization of wages of the U.S. labor market stopped during 2000–2016 as the wage of low-wage decreased relative to that of middle-wage occupations, whereas employment polarization continued. RBTC, which seems to have continued during this period, cannot alone account for these facts. I argue that occupation-specific human capital is key to understanding the onset and the end of wage polarization and I present the following motivating facts related to the accumulation of human capital in the three broad occupational groups:

1. Young workers increasingly work in low-wage occupations.

2. Wages grow less with age in low-wage than in the other occupations.

3. Occupational mobility was lower during 2000–2016.

In Section 3 I present a model to disentangle the role of each of these forces in shaping the trends in employment and wage polarization from 1980 to 2016.

3 Model

To account for each of the forces discussed in the previous Section I need to consider several factors simultaneously. First, I need to isolate the effect of RBTC change during 1980–2000 and during 2000–2016. Second, I need to account for differences in human capital growth within occupations, as well as the differences in the human capital of young workers across time, which are not observable. Finally, to consider occupational mobility I need measure how much of their human capital workers can transfer across occupations. I consider all these forces by developing a general equilibrium model with the following key features: (i) production combines labor inputs from occupations affected by occupation-based technical change; (ii) workers accumulate human capital according to their occupation and idiosyncratic shocks; (iii) workers can move across occupations and when they move they can only transfer a fraction of their human capital.

3.1 Technology

Time is discrete and runs forever. There is one homogeneous good that is produced combining the labor services of workers in high-wage, middle-wage and low-wage occupations (H_j) with a CES technology:[27]

$$Y = \left[(A_h H_h)^{\frac{\sigma-1}{\sigma}} + (A_m H_m)^{\frac{\sigma-1}{\sigma}} + (A_l H_l)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where A_j is occupation-specific labor-augmenting technological progress and σ is the elasticity of substitution of the the different occupations. If $\sigma \in [0, 1)$ the labor services of the occupations are complements in production, if $\sigma = 1$ the production function is Cobb-Douglas and if $\sigma > 1$ the labor services of the occupations are substitutes.

I assume that $\sigma < 1$ as the labor inputs are supplied by broad occupational groups and therefore are likely to complements. For example, an accountant from high-wage, a production worker from middle-wage, and a janitor from low-wage occupations perform tasks that are complementary in production.[28]

If $\{w_h, w_m, w_l\}$ are the unit wages paid to workers in each occupation, for occupation i and j the first-order conditions of the problem of the representative firm imply:

$$\left(\frac{A_j}{A_i}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{H_j}{H_i}\right)^{-\frac{1}{\sigma}} = \frac{w_j}{w_i} \tag{3}$$

which determines the relative demand of labor services, given the relative occupation-specific labor-augmenting technological progress and the relative unit wages of occupations i and j.

3.2 Workers

To model the behavior of workers I follow the dynamic Roy model developed by Dvorkin and Monge-Naranjo (2019). In the economy there is a measure one of workers at each time t. Each period a random fraction δ of the ("older") workers die and are replaced by new ("young") workers

[27] Because I focus on the consequences but not on the sources of occupation-biased technical change –RBTC more specifically– I do not explicitly include physical capital in the model. The main implication of this assumption is that the changes in occupation-specific labor-augmenting technological progress include both changes in total factor productivity (TFP) of each occupation as well as the differential effects of changes in the accumulation of physical capital due to different capital intensities in each occupation. Also, Bárány and Siegel (2018) show that structural change –the shift from manufacturing to the service sector– seems to have driven the polarization of the U.S. labor market as the demand for services, intensive in non-routine occupations, increases. Since I don't model the demand for goods and services, this force will also be identified as changes in the occupation-specific labor augmenting technological progress. Moreover, structural change has been a consistent phenomenon during 1980–2016 but I focus on the end of wage polarization during 2000–2016, suggesting that this is the result of other force that changed during this period.

[28] The complementarity of routine, non-routine manual and non-routine cognitive tasks in production is a common assumption in the polarization literature. See for example Autor and Dorn (2013).

that enter the labor market. The present discounted lifetime utility of workers takes following C.R.R.A. form:

$$U(c) = \sum_{t=0}^{\infty} (\beta(1-\delta))^t \frac{c_t^{1-\gamma}}{1-\gamma} \tag{4}$$

where $\beta \in (0,1)$ is the discount factor, $\gamma \geq 0$ is the coefficient of relative risk aversion.

Older workers start each period in an occupation j with a level h of human capital. At the beginning of each period they draw a vector of idiosyncratic occupational productivity shocks: $\boldsymbol{\epsilon}_t = [\epsilon_c, \epsilon_r, \epsilon_m]$, which determine their comparative advantage in each occupation. These shocks are distributed Fréchet with location parameter λ_j, common shape parameter α; independently across occupations, time, and workers. A worker in occupation j with productivity shock ϵ_j and human capital h has labor earnings equal to $w_j \epsilon_j h$.

At the end of each period workers choose an occupation k in which –if alive– they will work in the next period with a level of human capital equal to:

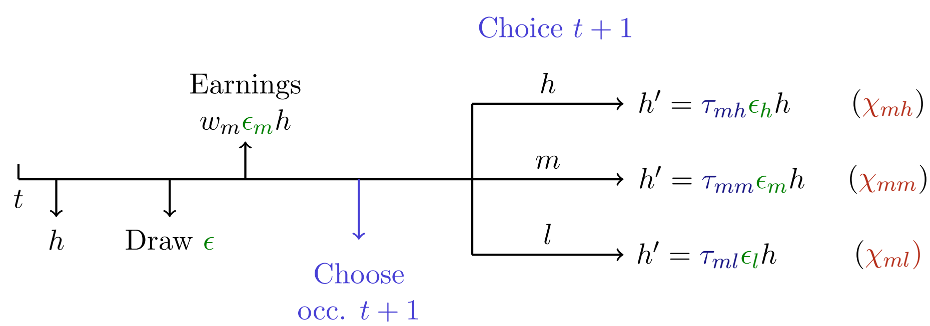
$$h' = h * \epsilon_k * \tau_{jk} \tag{5}$$

where $\tau_{jk} > 0$ measures how transferable is the human capital of a worker moving from occupation j to occupation k.

From Equation 5, the idiosyncratic productivity shocks not only determine labor earnings but also impact the productivity of workers to accumulate human capital in each occupation. These shocks also have a key role in shaping the patterns of occupational mobility, as workers who draw higher ϵ_k are more likely to transition to occupation k. The parameter τ_{jk} summarizes how much of the human capital is specific to occupation j and how much can be transferred to occupation k. If $\tau_{jk} \in (0,1]$, human capital depreciates when moving from j to k, if $\tau_{jk} \geq 1$ human capital (weakly) increases when moving from j to k. The parameters τ_{jj} govern the average human capital growth in occupation j. Because workers' wages in an occupation tend to grow over the life-cycle, we would expect τ_{jj} to be greater than one. On the other hand, several τ_{jk} are likely to be less than one as part of the human capital that workers accumulate is very specific and might not be useful in another occupation. Also, for a worker that moves to a new occupation it might take time to master all the tasks that he needs to perform. For example, for a worker transitioning from being a bus driver to a clerical occupation his knowledge on how to drive a bus is useless, while he might have to learn how to operate certain computer software required in his new occupation. On the other hand, some τ_{jk} can be greater than one as some transitions occur because workers are promoted, obtain training or acquire education –e.g. production workers to managers, clerical workers to professional occupations–, that reflect an increase in their human capital. When moving from occupation j to k workers also face non-pecuniary costs $\chi_{jk} > 0$, which are assumed to be proportional to the expected lifetime utility in occupation k at time t. These non-pecuniary costs capture all the factors that influence the occupational decision and that do not have a direct impact on workers' earnings –e.g. preferences for work schedules, physical activity, working environment, training and licensing requirements–.

Figure 6 summarizes the problem of a worker that starts the period in middle-wage occupations with a level of human capital h.

Figure 6: Older workers' choices



Young workers start with a level of human capital $h_0 = 1$ and face a similar problem than that of older workers. In the period before entering the labor market, they are not attached to any occupation. From the same Fréchet distributions as the older workers they draw occupational productivity shocks $\boldsymbol{\epsilon}_t$, which determine their comparative advantage for the next period. They choose the occupation j that maximizes their lifetime earnings. In the first period they earn $w_j * \epsilon_j * \tau_j^0 * h_0$ and their human capital is:

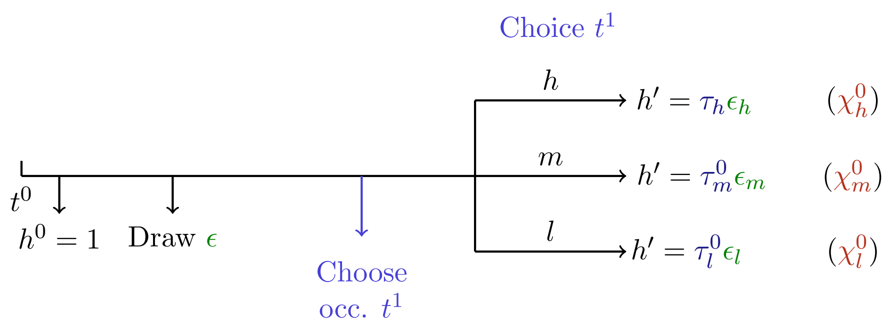
$$h^1 = \epsilon_j * \tau_j^0 \tag{6}$$

where τ_j^0 is the transferability of the initial human capital to occupation j.

The parameters τ_j^0 capture heterogeneity in the human capital of young workers that sort into each of the occupations at the moment they join the labor market. This heterogeneity can arise due to differences in ability, education, training and the knowledge of young workers to perform the tasks required in the occupation. Young workers also face non-pecuniary costs χ_j^0 to join each occupation. These non-pecuniary costs capture preferences for different amenities and characteristics of each occupation, which might be different than those of older workers –e.g. flexible work schedules, training and education opportunities–.

Figure 7 summarizes the problem of young workers.

Figure 7: Young workers' choices



The problem of older workers in recursive form is:

$$V(j, h, \boldsymbol{\epsilon}) = \frac{(w_j h \epsilon_j)^{1-\gamma}}{1-\gamma} + \beta(1-\delta) \max_k \{\chi_{jk} E_{\epsilon'} V(k, h', \boldsymbol{\epsilon}')\} \tag{7}$$

where the level of human capital h summarizes all the past occupational choices and realizations of idiosyncratic shocks.

Because of the the homogeneity of the C.R.R.A. utility function $(1-\gamma)$, the log-linear law of motion of human capital and the independence of the productivity shocks we can express this Bellman Equation as:[29]

$$v(j, \boldsymbol{\epsilon}) = \frac{(w_j \epsilon_j)^{1-\gamma}}{1-\gamma} + \beta(1-\delta) \max_l \{\chi_{jk} E_{\epsilon'}[v(k, \boldsymbol{\epsilon}')](\tau_{jk}\epsilon_k)^{1-\gamma}\} \tag{8}$$

Equation 8 is a key result from Dvorkin and Monge-Naranjo (2019) and shows how tractable this model is: to characterize the equilibrium of the economy we do not need to keep track of the

[29]See Lemma 1 of Dvorkin and Monge-Naranjo (2019).

level of human capital or its distribution; the comparative advantage of workers is determined by (i) their current occupation (j), and (ii) their idiosyncratic productivity shocks ($\boldsymbol{\epsilon}$).

For $\gamma > 1$, which implies risk-averse workers –a standard assumption in quantitative macro–, the unique solution v_j to this Bellman Equation is:[30]

$$v_j = \lambda_j^{1-\gamma}\Gamma\left(1 + \frac{1}{\alpha/(1-\gamma)}\right)\frac{w_j^{1-\gamma}}{1-\gamma} - \beta\Gamma\left(1 - \frac{1-\gamma}{\alpha}\right)\left[\sum_{k=1}^{3}(-\chi_{jk}v_k)^{\frac{\alpha}{1-\gamma}}(\tau_{jk}\lambda_k)^{\alpha}\right]^{\frac{1-\gamma}{\alpha}} \tag{9}$$

. where Γ is the gamma function and $v_j < 0$.

The share of workers who move from occupation j to occupation k each period is:

$$\mu_{jk} = \frac{\left[\lambda_k\tau_{jk}(-\chi_{jk}v_k)^{\frac{1}{1-\gamma}}\right]^{\alpha}}{\sum_{l=1}^{3}\left[\lambda_l\tau_{jl}(-\chi_{jl}v_l)^{\frac{1}{1-\gamma}}\right]^{\alpha}} \tag{10}$$

where higher average productivity shocks for occupation k –i.e. higher location parameter of the Fréchet distribution, λ_k–, higher transferability of the human capital, lower non-pecuniary costs, and higher value of the occupation k have a direct positive effect on the share of workers that transition from j to k.

The share of human capital moving from occupation j to occupation k each period is:

$$M_{jk} = \underbrace{\Gamma\left(1 - \frac{1}{\alpha}\right)\lambda_k \overbrace{\mu_{jk}^{-\frac{1}{\alpha}}}^{\text{Selection (-)}}}_{\text{Expected shock (+)}} \underbrace{\mu_{jk}}_{\text{Mobility (+)}} \underbrace{\tau_{jk}}_{\text{Transferability (+)}} \tag{11}$$

which is increasing in the expected productivity shock that workers draw, conditional on moving from j to k. The term $\Gamma\left(1 - \frac{1}{\alpha}\right)\lambda_k$ is the mean of the Fréchet productivity shock for occupation k. The term $\mu_{jk}^{-\frac{1}{\alpha}}$ is a negative selection effect; as the share of workers transitioning from j to k increases workers with lower productivity shocks make this transition. But, at the same time, the total mass of human capital transitioning from j to k increases and for $\alpha > 1$ this effect is higher than the negative selection effect. Finally, with higher τ_{jk} human capital in occupation j is more transferable to occupation k.

[30] See Lemma 1 and Theorem 1 of Dvorkin and Monge-Naranjo (2019).

The average human capital brought by workers moving from j to k is:

$$\bar{h}'_{jk} = \frac{M_{jk}}{\mu_{jk}} \bar{h}_j \tag{12}$$

where $\frac{M_{jk}}{\mu_{jk}}$ is the average change in the human capital of the workers transitioning and $\bar{h}_j$ is the average human capital of workers in the origin occupation j. Dividing Equation 11 by the share of workers that move from j to k, we see that because of the negative selection effect the average change in human capital decreases as more workers make this transition.

Similar to Equation 10 the employment shares of young workers are:

$$\theta_j^0 = \frac{\left[\lambda_j \tau_j^0 (-\chi_j^0 v_j)^{\frac{1}{1-\gamma}}\right]^{\alpha}}{\left[\sum_{k=1}^{J} \lambda_k \tau_k^0 (-\chi_k^0 v_k)^{\frac{1}{1-\gamma}}\right]^{\alpha}} \tag{13}$$

which is increasing in the transferability of the human capital of young workers to occupation j and decreasing in their non-pecuniary costs for this occupation. Changes in λ_j and v_j also have a direct positive effect in the share of young workers in occupation j.

The initial human capital in occupation j is higher when the expected productivity shock of young workers is higher, when more young workers sort into this occupation and when they can transfer more of their initial human capital. Similar to Equation 12 this expression is equal to:

$$H_j^0 = \underbrace{\Gamma\left(1 - \frac{1}{\alpha}\right) \lambda_j \overbrace{[\theta_j^0]^{-\frac{1}{\alpha}}}^{\text{Selection (-)}}}_{\text{Expected shock (+)}} \underbrace{\theta_j^0}_{\text{Share (+)}} \underbrace{\tau_j^0}_{\text{Transferability (+)}} \tag{14}$$

Finally, the average human capital of young workers in occupation j is:

$$\bar{h}_j^0 = \frac{H_j^0}{\theta_j^0} \tag{15}$$

which is also decreasing in the share of young workers who select into the occupation due to a negative selection effect that decreases their average comparative advantage.

3.3 Stationary Distributions

After entering the labor market the employment shares of a cohort of young workers evolve according to the matrix $\boldsymbol{\mu}$ of pairwise transitions. Hence, for period 1 and for any period $s > 1$ the employment shares of a cohort evolve as:

$$\boldsymbol{\theta}^1 = (1-\delta)\boldsymbol{\theta}^0\boldsymbol{\mu} \quad \Longrightarrow \quad \boldsymbol{\theta}^s = (1-\delta)\boldsymbol{\theta}^{s-1}\boldsymbol{\mu}$$

which iterating converges to:

$$\boldsymbol{\theta} = \delta\boldsymbol{\theta}^0[\boldsymbol{I} - (1-\delta)\boldsymbol{\mu}]^{-1} \tag{16}$$

This vector exists, is unique and well defined because $\boldsymbol{\mu}$ has a highest possible eigenvalue of 1 as its entries are shares between zero and one.

Similarly, the human capital of a cohort in each occupation evolves according to the matrix $\boldsymbol{M}$ of pairwise transitions. For period 1 and any period $s > 1$ the human capital of a cohort evolves as:

$$\boldsymbol{H}^1 = (1-\delta)\boldsymbol{H}^0\boldsymbol{M} \quad \Longrightarrow \quad \boldsymbol{H}^s = (1-\delta)\boldsymbol{H}^{s-1}\boldsymbol{M}$$

which iterating converges to:

$$\boldsymbol{H} = \delta\boldsymbol{H}^0[\boldsymbol{I} - (1-\delta)\boldsymbol{M}]^{-1} \tag{17}$$

$\boldsymbol{H}$ may not be well defined. If the growth of the human capital of the workers that survive each period is higher than that of those that die, then there is not an invariant distribution of human capital and it grows over time. In this case there exists a unique balanced growth path of the aggregate human capital and the human capital of each occupation in equilibrium converges to stable ratios (H_j/H_i).[31]

3.4 Competitive Equilibrium

Given an initial population of workers, their human capital and occupational choices $\{\theta_j^0, H_j^0\}_{j=1}^J$, and exogenous labor-augmenting technological progress $\{A_j\}_{j=1}^J$, an equilibrium is:

i) Wages: w_j.

[31] See Proposition 1 of Dvorkin and Monge-Naranjo (2019).

ii) Workers' occupational decisions: v_j, μ_j.

iii) Aggregate demands of human capital: H_j.

such that given wages:

1. Workers optimal decisions are given by v_j and μ.

2. Labor markets clear.

3.5 Discussion

The analysis of the polarization of the labor market focuses on employment shares and average occupational wages. The model counterpart of the employment shares are given by Equation 16 and average occupational wages are given by:

$$\bar{w}_j = w_j \frac{H_j}{\theta_j} = w_j \bar{h}_j \tag{18}$$

where $\bar{h}_j$ is the average human capital in occupation j. Thus, in the model changes in average occupational wages can be decomposed into changes in the unit wages and changes in the average human capital of occupations.

Changes in the parameters of the model affect workers' choices through changes in the value of the occupations. Because workers can move across occupations the changes in the parameters of one occupation affect workers in all occupations. For example, an increase in λ_j increases earnings and human capital accumulation for workers in j but also increases the value of moving to j from the other occupations. From the continuation values of Equation 9, if $(-\chi_{jj})^{\frac{1}{1-\gamma}}\tau_{jj} \geq (-\chi_{kj})^{\frac{1}{1-\gamma}}\tau_{kj}$ the effect of changes in the parameters of j in the value of moving from j to k is relatively lower than the effect of staying in j. Thus, when the parameters of occupation j change the value of j, v_j, increases relatively more than that of k, v_k. Intuitively, this condition implies that the costs of staying in occupation j are relatively low compared to those faced by workers transitioning from other occupation k.

Occupation-biased technical change towards occupation j occurs when the occupation-specific labor-augmenting technological progress increases relative to the other occupations ($\uparrow \frac{A_j}{A_i}, i \neq j$). This increases the relative effective supply of the labor services of occupation j, generating an excess of supply. This excess of relative supply reduces the left-hand side of Equation 3 because the labor inputs of the occupations are complements ($\sigma < 1$). To restore equilibrium, the relative supply of labor services of occupation j ($\frac{H_j}{H_i}$) needs to decrease. Thus, the relative unit wage of j to i ($\frac{w_j}{w_i}$) has to decrease, which increases the relative value of occupation i. This leads to an increase in the human capital and the employment share of young workers that sort into occupation i; see Equations 14 and 13. The shares of employment and human capital of workers transitioning from j to i increase as well, whereas these shares from i to j decrease; see Equations 10 and 11. These changes increase the relative supply of human capital of occupation i, eliminating the excess in supply of j.

Hence, as predicted by the literature, occupation j-biased technical change increases the employment share of the other occupations but, what happens with average wages is ambiguous. On the one hand, the relative unit wages of occupation j decrease. On the other hand, from Equation 15 the average human capital of young workers in occupation j increases while that in the other occupations decreases. Also, the average change in the human capital of workers transitioning from j to the other occupations goes down while that of those transitioning to j increases; see Equation 12. The mechanism behind these changes is the selection of workers: as the share of workers that select into occupation j decreases, the average worker has a higher comparative advantage while the opposite occurs with the other occupations.

4 Calibration

In the following Sections my goal is to analyze the role of technology, human capital accumulation and occupational mobility in the onset and the end of wage polarization. To do so, I compare three equilibria of the model, meant to represent the U.S. economy in 1980, 2000 and 2016. The exogenous factors that differ between the three equilibria are:

i) Labor-augmenting technological progress (A_j).

ii) Productivity shocks (λ_j).

iii) Transferability of HK and non-pecuniary costs of young workers (τ_j^0, χ_j^0).

iv) Transferability of HK and non-pecuniary costs of older worlers (τ_{jk}, χ_{jk}).

Given these exogenous factors, in each equilibrium workers make their optimal occupational choices and determine the distribution of employment and human capital which, together with the equilibrium wages per unit of human capital, determine occupational wages.

In the remainder of this Section I describe the empirical strategy. Table 2 summarizes five time-invariant parameters and five normalizations. For the five time-invariant parameters I choose standard values in the literature: $\beta = 0.95$, $\gamma = 2$, $\sigma = 0.56$ from Duernecker and Herrendorf (2017) and Bárány and Siegel (2020), and $\alpha = 13$, $\delta = 0.03$ from Dvorkin and Monge-Naranjo (2019). The first two normalizations are required because I focus on the wages of low- and high-wage relative to middle-wage occupations. I normalize the transferability of the human capital of young workers to middle-wage, $\tau_m^0 = 1$, so that to high- and low-wage occupations is relative to middle-wage. I set the location parameter of the productivity shock, λ_m, such that the average human capital of workers that stay in middle-wage occupations does not grow, $\frac{M_{mm}}{\mu_{mm}} = 1$. This assumption does not affect the equilibrium allocation and relative wages but implies that human capital growth for the other transitions is relative to that of the workers staying in middle-wage occupations. The last three normalizations are required to have enough degrees of freedom to calibrate the model.[32] I normalize the non-pecuniary cost of young workers for middle-wage, $\chi_m^0 = 1$, such that those for high- and low-wage occupations are relative to middle-wage. I set the non-pecuniary costs of changing occupation, $\chi_{jk} = 1$, which implies that I estimate non-pecuniary costs of staying in an occupation relative to moving to any occupation. Finally, human capital growth for stayers is governed only by the productivity shocks as I fix the transferability of human capital within an occupation, $\tau_{jj} = 1$. From the last assumption, the estimated transferability of human capital to other occupations is also interpreted as relative to that of workers that stay in an occupation.

In Table 3 I summarize the seventeen parameters that I calibrate jointly: λ_l, λ_h, τ_l^0, τ_h^0, χ_l^0, χ_h^0, χ_{ll}, χ_{mm}, χ_{hh}, τ_{lm}, τ_{lh}, τ_{ml}, τ_{mh}, τ_{hl}, τ_{hm}, A_m/A_l, A_m/A_h to match seventeen data moments in 1980, 2000 and 2016: (i-ii) average wage, relative to middle-wage, of workers in low- and high-wage occupations; (iii-iv) average wage, relative to middle-wage, of 16–24 year old workers in low- and high-wage occupations; (v-vi) employment share of 16–24 year old workers in low- and high-wage

[32] The first normalization arises because I estimate the non-pecuniary costs of young workers by matching their employment shares. The second normalization arises because χ_{jk} affect the mobility of workers and from Equation 16 I match $\boldsymbol{\theta}$, $\boldsymbol{\theta}^0$ and μ_{jj}, which makes μ_{jk} endogenous. Finally, τ_{jj} cannot be pinned down separately from λ_j as both affect human capital growth within each occupation.

Table 2: Time-invariant Parameters and Normalizations

Parameter		Value
Time-invariant		
Discount factor	β	0.95
Relative risk aversion	γ	2
Elasticity of substitution	σ	0.56
Shape of productivity shocks	α	13
Normalizations		
Transferability HK of young in middle-wage	τ_m^0	1
HK growth in middle-wage	$\frac{M_{mm}}{\mu_{mm}}$	1
Non-pecuniary cost of middle-wage for young	χ_m^0	1
Non-pecuniary costs of mobility	χ_{jk}	1
Transferability of HK within occupations	τ_{jj}	1

occupations; (vii-ix) percentage of workers staying in each occupation per year; (x-xv) transition of earnings across different occupations, relative to the average wage growth in middle-wage, (xvi-xvii) employment share of workers in low- and high-wage occupations. The relative average wages and the employment shares are calculated using the Census 1980, 2000, and ACS 2014–2018. The percentage of stayers and the transition of earnings are calculated from the PSID for the years 1973–1979 for 1980, 1993–1999 for 2000 and 2011–2017 for the 2016 sample. The transition of earnings across occupations are calculated by multiplying the matrix of average wage changes for all transitions by the matrix of transition shares. I normalize the transition of earnings by the average wage growth within middle-wage occupations, such that $M_{mm}/\mu_{mm} = 1$.

Figure 8 shows that I match the targets well.[33] The percentage of workers that stay in each occupation are relatively more difficult to match because the PSID and Census/ACS samples are

[33]Table 9 in Appendix A.6 shows the values of the targets and the model predictions.

Table 3: Joint Calibration

Parameter		Moment	
Location of productivity shocks	λ_j	Average relative wage	$\bar{w}_j/\bar{w}_m$
Transferability HK for young	τ_j^0	Average relative wage of 16-24 years old	$\bar{w}_j^0/\bar{w}_m^0$
Non-pecuniary cost for young	χ_j^0	Employment share of 16-24 years old	θ_j^0
Transferability HK	τ_{ik}	Transition of earnings*	$\frac{w_k}{w_i}M_{ik}$
Non-pecuniary cost	χ_{ii}	Percentage of workers staying	μ_{jj}
Occupation-specific technical change	A_m/A_j	Employment share	θ_j

Notes: $j \in$ {high-wage, low-wage}, $i, k \in$ {high-wage, middle-wage, low-wage}.
*Normalized with respect to the average wage growth of workers staying in middle-wage occupations.

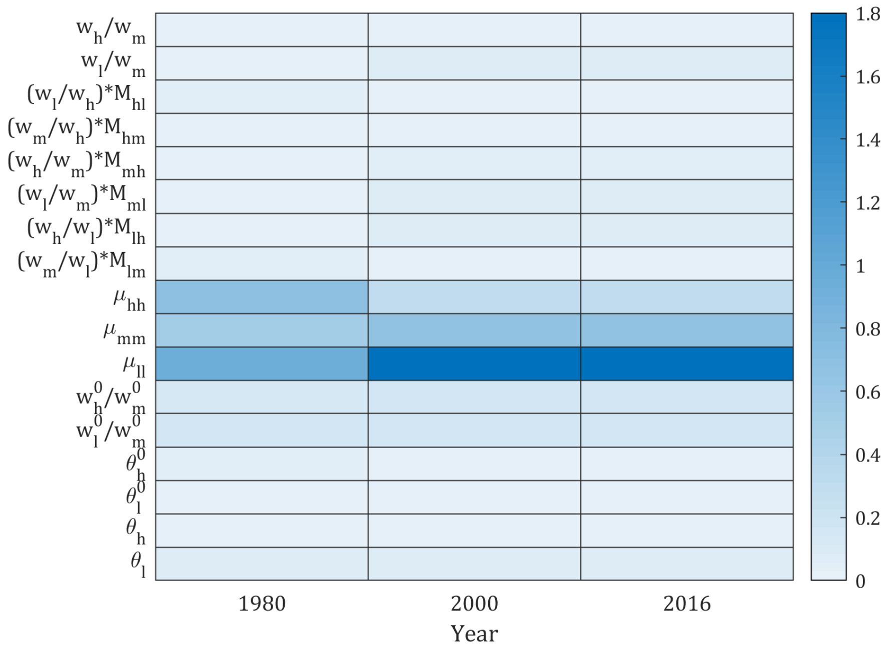
slightly different due to data limitations. For example, the PSID sample is restricted to heads of household and does not include immigrants that arrived to the U.S. after 1968. Therefore, the employment shares of young workers and the stationary distribution of employment, both calculated from the Census and ACS, may not be entirely consistent with the percentage of workers staying in each occupation, calculated from the PSID. Nevertheless, as I show in Figure 17 of Appendix A.7, the model performs reasonably well matching the trends in the mobility to and from all occupations that I did not target.

In Appendix A.8 I show the estimated parameters for each year.

5 Results

In this Section, I present the main results of this paper. In the first subsection, I describe the baseline economy estimated with the targeted moments in 1980. In the second subsection, I analyze the evolution of occupation-biased technical change and the relative unit wages of low- and high-wage occupations during 1980–2000 and 2000–2016. Finally, in the last subsection I discuss the changes in the human capital of low- and high-wage occupations, relative to that of middle-wage, during these periods.

Figure 8: Absolute Error of Targeted Moments. Years 1980, 2000 and 2016



Notes: for data moment x and model moment $\hat{x}$ the statistic is $|x - \hat{x}|/x$.

5.1 Baseline Economy

Table 4 shows that in 1980 the average human capital of young workers in low-wage was the highest and in middle-wage occupations was the lowest. From Equations 13 and 14 there are two forces that determine these differences: (i) conditional expectation of the productivity shock; (ii) the transferability of human capital of young workers to the occupation. The average human capital of young workers in middle-wage occupations is lower because their average comparative advantage is low as most workers sort into middle-wage occupations (73.7%). The expected productivity shock is higher for high- and low-wage occupations but for two different reasons. For high-wage, the average of the Fréchet distribution from which workers draw these shocks is higher, thanks to a higher estimated λ_h. For low-wage occupations, there is strong positive selection: the marginal young worker in that occupation has high comparative advantage because few young workers sort into low-wage occupations –10.5% compared to 15.8% in high-wage–. The transferability of the human capital of young workers is the highest in low-wage occupations –1.059 relative to middle-wage– whereas in high-wage occupations is the lowest –0.945 relative to middle-wage–.

A plausible explanation for the lower initial human capital of workers in high-wage is that many of the young workers that join the labor market in these occupations have not yet acquired the specific human capital required to perform the tasks in these occupations. High-wage occupations mostly require workers to perform complex cognitive tasks –e.g. programming, analyzing information, presenting– which take time to master and doing so generally requires specific training or formal education. In line with this hypothesis, only 29.0% of young workers in high-wage occupations had a college degree, compared to 48.8% among older workers. On the other hand, many low-wage occupations are characterized by manual tasks –e.g. mopping, serving food, preparing cocktails– that do not require specific training or formal education, which can be mastered faster and can therefore explain the relatively higher transferability of human capital.

Table 4: Human Capital Relative to Middle-wage Occupations. Year 1980

	Low-wage	High-wage
Average HK Young	1.211	1.072
HK Growth	0.986	1.008
Average HK Steady State	1.149	1.333

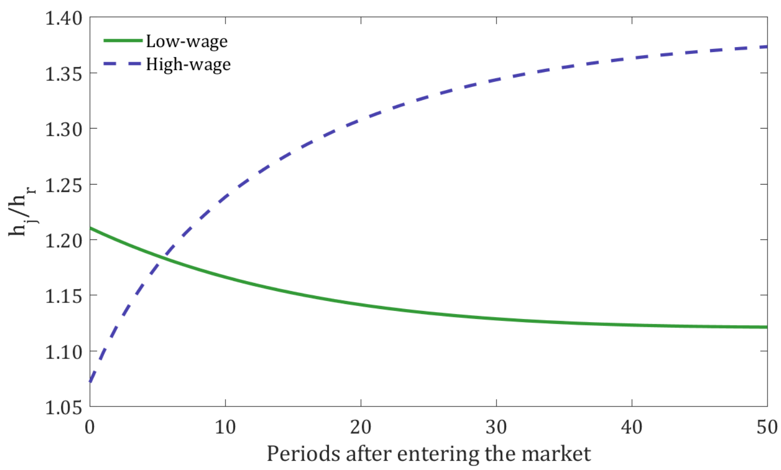
Notes: the table shows for low- and high-wage occupations the average human capital of young workers, human capital growth and the average human capital in steady-state relative to middle-wage occupations.

Transitioning from non-routine to routine occupations is costly in terms of human capital: workers from high- and low-wage occupations only keep around 67% of their human capital. Also, the workers who transition from high-wage to low-wage occupations keep relatively more human capital than those who do the opposite but in both cases there are substantial loses –0.786 vs. 0.612 per unit–. On the other hand, those who transition from middle- to high- and low-wage occupations suffer small loses in their human capital –0.995 and 0.940, respectively–. Part of this high transferability can be related to some workers transitioning to occupations where they perform similar tasks. Some of the routine occupations, such as secretaries and sales representatives, are referred to as "routine-cognitive" because they also require performing several cognitive tasks, whereas the rest, such as miners and machine operators, are generally referred to as "routine-manual" because they also require performing several manual tasks (Acemoglu and Autor, 2011). More than 75% of the transitions from middle- to low-wage (manual) occupations are from routine-manual and almost 55% of the transitions to high-wage (cognitive) are from routine-cognitive occupations. Also, 70% of the transitions to high-wage from routine-manual are promotions to managerial occupations where we would expect little human capital depreciation.

Table 4 also shows that average human capital in steady state, relative to middle-wage occupations, is lower than that of young workers in low-wage and higher in high-wage occupations. These changes are the result of differences in the growth of human capital in each occupation and the flow of human capital across occupations due to the mobility of workers. Human capital growth is higher in high-wage and lower in low-wage occupations, compared to middle-wage. The differences in human capital growth can also be explained by the differences in the tasks that workers perform in each occupation. Because many manual tasks in low-wage occupations can be mastered relatively quickly we would expect human capital accumulation to be lower for workers in these occupations as they soon do not have much to learn. On the other hand, cognitive tasks tend to take time to master so workers in high-wage occupations are more likely to learn more in their occupations and accumulate more human capital. Finally, workers in middle-wage perform routine-cognitive and routine-manual tasks so human capital growth is somewhere in-between that of low- and high-wage occupations.

To discuss the effect of occupational mobility in the accumulation of human capital, in Figure 9 I show for a cohort of workers the evolution of the human capital in low- and high-wage, relative to middle-wage occupations, up to fifty periods after entering the labor market. Mobility has a sizable positive effect in the accumulation of human capital in low-wage occupations because only few workers with high productivity shocks transition from middle- and high-wage occupations. For example, one period after entering the labor market the workers that stay in these occupations have on average 98.6% of the human capital of those in middle-wage but when we also consider the workers that came from middle- and high-wage occupations that percentage increases to 99.4%. Figure 9 shows that as a cohort grows older the average human capital of workers in low-wage occupations relative to middle-wage falls but at a decreasing rate. The positive effect of occupational mobility becomes more important with time because the human capital of those transitioning from high- and middle-wage occupations is relatively higher, thanks to the higher human capital growth in these occupations. Low occupational mobility in 1980 has a positive effect in the accumulation of human capital in high-wage occupations during the first periods after a cohort enters the labor market because a high percentage of workers remain many periods in this occupations with high human capital growth. But, as the average human capital in high-wage increases, the workers transitioning from other occupations have relatively less human capital and slow down human capital accumulation.

Figure 9: Average Human Capital Relative to Middle-wage Occupations. Simulation of a Cohort. Year 1980



Notes: the figure shows for one cohort of workers the average human capital of those in low-wage and high-wage occupations relative to those in middle-wage occupations from the period they enter the labor market until fifty periods later.

5.2 Occupation-Biased Technical Change and Relative Unit Wages

In this subsection, I discuss the evolution of occupation-biased technical and the relative unit wages of high- and low-wage occupations during 1980–2000 and 2000–2016. Table 5 shows that RBTC happened during both periods as labor-augmenting technological progress was faster for middle-wage occupations ($\uparrow \frac{A_m}{A_j}$, $j \in \{l, h\}$). Thus, in line with the evidence discussed in Section 2, despite a slowdown compared to 1980–2000, RBTC was a strong force affecting the U.S. economy during 2000–2016, when wage polarization stopped. The Table also shows that during both periods technical change was faster for low-wage than for high-wage occupations, which follows the prediction of the polarization literature as cognitive tasks are more difficult to be translated into programmed instructions that machines can execute (Autor, Levy and Murane, 2003). Therefore, RBTC led to the increase of the employment shares of non-routine occupations during 1980–2016 as it increased the relative demand for non-routine labor services; see Equation 3.

Table 5: Occupation-biased Technical Change

	1980	2000	2016
A_m/A_h	0.324	1.214	3.219
A_m/A_l	0.011	0.022	0.041
A_h/A_l	0.033	0.018	0.013

Notes: the table shows the estimated relative occupation-biased technical change parameters in 1980, 2000 and 2016. l = low-wage, m = middle-wage, h = high-wage.

Figure 10 shows the equilibrium wages per-unit of human capital, relative to middle-wage occupations, for high- and low-wage occupations in the years 1980, 2000, and 2016. The relative wage for low-wage increased due to the effect of RBTC and because the changes in the accumulation of human capital, which I discuss in detail in Section 5, did not increase their total human capital relative to middle-wage occupations (H_l/H_m). For high-wage occupations their relative wage per-unit of human capital went down over time. For these occupations, the positive effect of RBTC was more than offset by more human capital accumulation that increased its total supply relative to middle-wage occupations (H_h/H_m). Thus, the evolution of relative wages drove the relative average wage of high-wage occupations downwards and that of low-wage occupations upwards during both periods. Therefore, these changes cannot explain the onset and the end of wage polarization as described in Table 1 of Section 2. To understand this phenomena, in the following subsection I analyze the changes in occupational human capital over time.

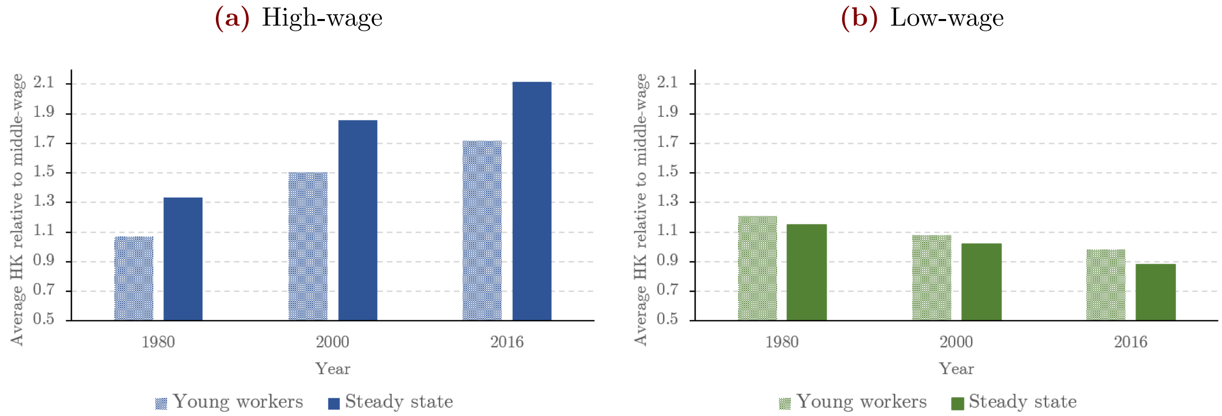
Figure 10: Relative Wage per-unit of Human Capital
High-wage and Low-wage Occupations. Years 1980, 2000, 2016

Notes: the figure shows the equilibrium wage per unit of human capital for low-wage and high-wage occupations, relative to middle-wage occupations ,w_j/w_m, calibrated in the years 1980, 2000, and 2016.

5.3 Changes in Human Capital

Figure 11 shows the average human capital of young workers and in steady-state, relative to that of workers in middle-wage occupations, for high-wage –left panel– and for low-wage occupations –right panel– in 1980, 2000 and 2016. The average human capital of workers in low-wage decreased from 1.15 times that of workers in middle-wage occupations in 1980 to 1.02 in 2000 and to 0.88 in 2016. Thus, the decrease in the relative average wage of low-wage occupations during 2000–2016, that led to the end of wage polarization, was due to a decrease in the average human capital of workers in those occupations, which was stronger than the increase in the relative wage per unit of human capital. On the other hand, for workers in high-wage occupations their average relative human capital increased steadily over time from 1.33 times that of workers in middle-wage in 1980 to 1.86 in 2000 and to 2.12 in 2016. This led to the increase in their average wage over time, despite the decrease in their relative wage per unit of human capital. These changes in the human capital of occupations can be decomposed into changes in the human capital of young workers and changes in the accumulation of human capital in each occupation. In the remainder of this subsection I discuss how the changes in each of these factors affected the relative human capital of high- and low-wage relative to middle-wage occupations.

Figure 11: Average Human Capital Relative to Middle-wage Occupations. Young workers and Steady-state. Years 1980, 2000 and 2016



Notes: the left panel of the figure shows the average human capital of young workers and in steady-state for high-wage occupations in the years 1980, 2000 and 2016, and the right panel shows the same variables for the same years for low-wage occupations.

During 1980–2016, the decrease in the human capital of young workers who join the labor market in low-wage –together with the increase in the share of young workers in this occupations documented in Section 2– acted as an important force to decrease their relative average wage. On the contrary, for high-wage occupations the increase in the average human capital of young workers was one of the forces behind higher average relative wages over time. Figure 11 shows that the human capital of young workers in high-wage increased from 1.07 to 1.72 and in low-wage decreased from 1.21 to 0.98, relative to that in middle-wage occupations.

Table 6 shows the changes in the average comparative advantage –conditional expectation of the productivity shock– and the changes in the initial human capital –transferability of the initial human capital– of young workers in low- and high-wage, relative to middle-wage occupations. For low-wage occupations the changes in both variables contributed to the decrease in the human capital of young workers. The distribution of the productivity shocks for was relatively stable over time, as the estimated location parameter (λ_l) was similar at each point in time. Therefore, for a fixed distribution, the average comparative advantage of young workers went down because, as their relative unit wage increased, a higher share sorted into these occupations decreasing the productivity shock of the marginal worker. One interpretation for the lower transferability of the human capital of young workers in low-wage over time is that because of the higher relative unit wage an increasing number workers with low human capital, who in 1980 would have entered the labor market in middle-wage occupations, now sort into low-wage instead.[34] Moreover, according to the estimated parameters, low-wage occupations have relatively low non-pecuniary costs –see Table 10 in Appendix A.8– which makes this occupation even more attractive for young workers with low human capital. Also, during 1980–2016 the share of young workers with at least some college education in low- and in middle-wage occupations increased around 20 percentage points but the average wage of these workers in low-wage relative to middle-wage increased only from 0.845 to 0.859, less than that of those without college education –from 0.785 to 0.837–. This suggests that the relative human capital of workers with at least some college education in low-wage fell more than that of those without college education. Workers with college education may not be a good match for low-wage occupations, much of what they learn in college is not directly related to the type of manual tasks that they perform in low-wage occupations. This hypothesis is in line with a growing literature that shows that the mismatch between the tasks required by an occupation and the skills of the workers for performing and learning how to perform these tasks is important to explain the evolution of wages.[35]

Table 6 also shows that for high-wage occupations the increase in the average human capital of young workers was mostly due to a considerable increase in the transferability of their human capital. This is consistent with a higher share of young workers with a college degree, from 29.0% in 1980 to 53.0% in 2016 as, contrary to low-wage, what workers learn in college is directly related to the cognitive tasks required in these occupations. The average comparative advantage of young workers in high-wage increased during 1980–2000 due to an increase in their average productivity shock. But during 2000–2016 a decrease in the average productivity shock amplified the negative effect of an increasing share workers with lower productivity shocks entering the labor market in high-wage occupations.

Figure 11 also shows that in each of the three years considered in the average human capital of workers in low-wage, relative to middle-wage, is lower than that of young workers whereas in high-wage it is higher. Thus, as suggested by Figure 3 of Section 2, human capital accumulation during 1980–2016 has been relatively lower in low-wage occupations, while in high-wage occupations

[34]This is a common hypothesis in the polarization literature. See for example Autor (2013), Cortes (2016), and Cortes, Jaimovich and Siu (2017).

[35]See for example Lindenlaub (2017), Guvenen et al. (2020) and Lise and Postel-Vinay (2020).

Table 6: Comparative Advantage and Transferability of Human Capital of Young Workers
Relative to Middle-wage Occupations
Years 1980, 2000, 2016

	1980	2000	2016
Expected Productivity Shock			
High-wage	1.134	1.151	1.100
Low-wage	1.144	1.088	1.050
Transferability of HK			
High-wage	0.945	1.308	1.561
Low-wage	1.059	0.992	0.934

Notes: the table shows the expected productivity shock for young workers, conditional on sorting into high- and low-wage occupations, and the transferability of their human capital into these occupations, in both cases relative to middle-wage occupations, for the years 1980, 2000 and 2016.

it has been relatively higher. To understand how the changes in human capital accumulation affected relative average wages I need to analyze the changes in the rate of human capital growth in each occupation and how these interacted with the changes in the flow of human capital across occupations due to changes in occupational mobility. Table 7 shows the rate of human capital growth for workers in low- and high-wage occupations, relative to those in middle-wage, in the years 1980, 2000 and 2016. These are mainly the result of changes in the distribution of the idiosyncratic productivity shocks, governed by the parameter λ_j. For low- and middle-wage occupations this distribution did not change much over time so human capital growth in the latter was 1.4% lower than that of the former in each of the years considered. For high-wage occupations the growth of human capital relative to that of middle-wage occupations increased during 1980–2000 and decreased during 2000–2016, but remained at higher levels than those in 1980.

To discuss the effect of occupational mobility in the changes of human capital accumulation

Table 7: Human Capital Growth
Relative to Middle-wage Occupations
Years 1980, 2000 and 2016

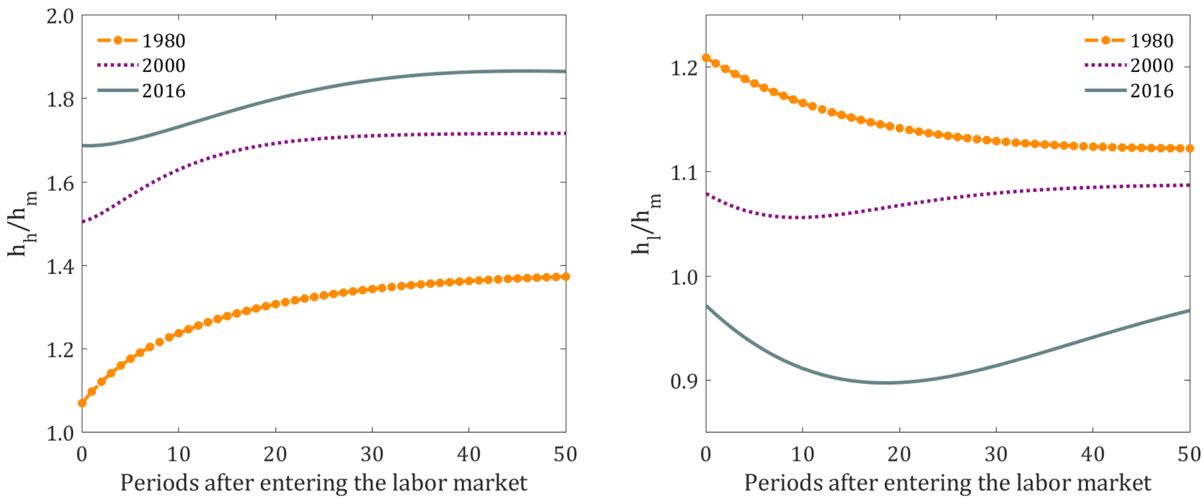
	1980	2000	2016
High-wage	1.008	1.042	1.020
Low-wage	0.986	0.986	0.986

Notes: the table shows the rate of human capital growth for workers in low- and high-wage occupations, relative to the growth for those in middle-wage occupations, in the years 1980, 2000 and 2016.

Figure 12 shows for a cohort of workers in 1980, 2000 and 2016 the evolution of the average human capital of those in high- –left panel– and low-wage –right panel–, relative to those in middle-wage occupation. The increase in occupational mobility during 1980–2000 had a positive effect on the accumulation of human capital in low-wage occupations and contributed to the increase in their average relative wage. The right panel of Figure 12 shows how as a cohort spends more time in the labor market the workers in low-wage occupations accumulate relatively more human capital and close the gap between their average human capital in 1980 and 2000, generated by the lower human capital of young workers. Compared to 1980, in 2000 fewer workers stay many periods in low-wage accumulating relatively less human capital; for example, in 1980 77.7% of workers remained in these occupations for at least five straight periods whereas in 2000 only 56.3% did so. Moreover, the increase in occupational mobility also led more workers with high human capital to transition from high- and middle-wage occupations. Like in 1980 the workers that make these transitions –1.1% and 1.2% in 2000 vs 0.3% and 0.5% in 1980 from high- and middle-wage, respectively– have a high comparative advantage. This high comparative advantage, together with the relatively higher human capital of workers in high- and middle-wage occupations, compensates a decrease in its estimated transferability ($\tau_{lj}, j \in \{h, m\}$; see Table 10). On the contrary, during 2000–2016 lower occupational mobility had a negative effect on the accumulation of human capital in low-wage occupations and contributed to the end of wage polarization. Now, workers in these occupations stay longer periods with relatively low human capital growth and fewer workers transition from high- and middle-wage occupations. Figure 12 illustrates this effect as the difference between the average relative human capital of workers in low-wage occupations in 2000 and 2016 widens as a cohort spends more time in the labor market.

Figure 12: Average Human Capital Relative to Middle-wage Occupations
Simulation of a Cohort. Years 1980, 2000 and 2016

(a) High-wage **(b)** Low-wage



Notes: the left panel of the figure plots for a cohort the average human capital of the workers in high-wage occupations, relative to those in middle-wage occupations, from the period they join the labor market until fifty periods later in the years 1980, 2000 and 2016. The right panel plots the same variable for the same years for low-wage occupations.

The left panel of Figure 12 shows that during 1980–2016 human capital accumulation in high-wage is higher than that in middle-wage occupations. The effect of changes in occupational mobility on the accumulation of human capital in high-wage the is opposite to that on low-wage because workers experience high human capital growth. Panel 12a stresses the importance of occupational mobility in the process of human capital accumulation of a cohort: while human capital growth in high-wage occupations increased importantly between 1980 and 2000 –from 0.8% to 4.2% higher than that of middle-wage– the negative effect of the increase in occupational mobility led to similar changes in the relative average human capital of workers in these occupations. During 2000–2016 lower human capital growth reduced human capital accumulation in high-wage, which can be observed in Panel 12a during the first ten periods of a cohort in the labor market, but as workers spend more periods in these occupations and fewer workers with low human capital transition from low- and middle-wage, the difference between the relative human capital in 2016 and that of 2000 increases.

The increase in occupational mobility during 1980–2000 is explained through an increase in the transferability of the human capital of low- to high- and middle-wage occupations and an increase in the non-pecuniary costs of staying in each of the occupations, while the transferbility of human capital from high- and middle- to low-wage occupations decreased –see Table 10–. During 2000–2016 the decrease in occupational mobility is explained almost exclusively through a considerable decrease in the non-pecuniary costs of staying in an occupation whereas the transferability of human capital remained at similar levels than in 2000. In line with the importance of non-pecuniary costs to determine the changes in occupational mobility, Böhm (2020) finds for the same occupational groups that differences in these costs are important to explain wage differences. Moreover, Cortes and Gallipoli (2017) find that some non-pecuniary costs such as training, unionization, and licensing requirements, explain a significant amount of the mobility patterns during 1994–2013. Also, Sorkin (2018) using employer-to-employer transitions during 2000–2008 estimates that compensating differentials are more than half of the firm component of the variance of earnings.

6 Counterfactuals

To better understand how the changes in the different forces in the model interacted over time, in Figure 13 I compare the observed employment shares and relative average wages for high- and low-wage occupations in 2000 and 2016 to four counterfactual. In each of these counterfactual only the following parameters change according to those estimated –see Table 10 for the specific values–: (i) occupation-biased technical change (A_j/A_i), (ii) transferability of the human capital of young workers (τ_j^0) and their non-pecuniary costs (χ_j^0), (iii) transferability of the human capital of older workers (τ_{jk}) and their non-pecuniary costs (χ_{jj}), (iv) productivity shocks (λ_j).

In the first counterfactual, which only allows for occupation-biased technical change, both in 2000 and 2016 the share of high-wage increases more than in the baseline and that of low-wage increases but less than in the baseline. The share of both occupations increases thanks to the positive effect of RBTC on the unit relative wages that attracted more workers to these occupations. The remaining counterfactuals, where occupation-specific labor-augmenting technological progress is constant over time, show the importance of RBTC to reallocate workers from routine to non-routine occupations. In all these counterfactuals the employment shares in 2000 and 2016 for high- and low-wage occupations are below those in the baseline economy for these years and around or below the 1980 shares.

But the right panels of Figure 13 show that if I only allow occupational-biased technical change to occur the average wage of both occupations, relative to middle-wage, is significantly lower than in the baseline economy in 2000 and 2016. This stresses the importance of the changes in human capital accumulation and its interaction with RBTC to explain the evolution of relative wages for these occupations. High-wage occupations have lower average relative wages because human capital growth does not increase over time, as the distribution of productivity shocks is stable over time, and because the human capital of young workers remains constant. For low-wage occupations the wage is lower because the relative unit wage increases significantly less. The forces that in the baseline economy decrease the accumulation of human capital in low-wage occupations decrease its relative supply and lead to an increase in the relative unit wage.

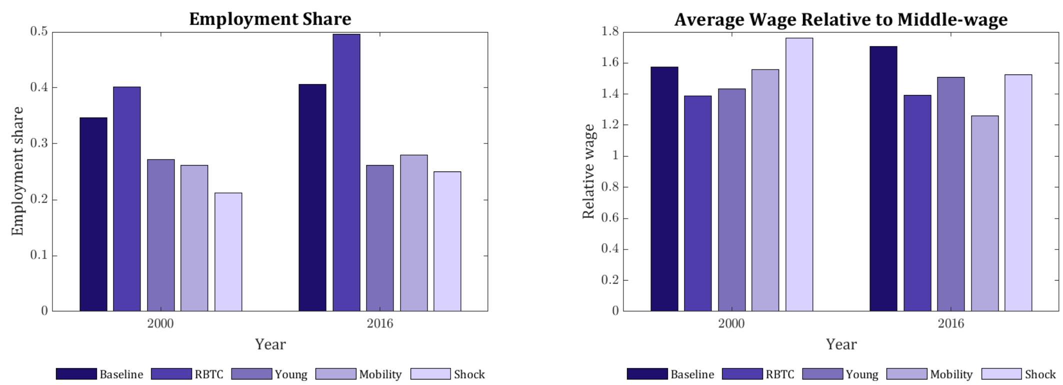
The remaining counterfactuals show how the changes in the other parameters and RBTC complement each other to explain the evolution of relative average wages. If only the transferability of the human capital of young workers and their non-pecuniary costs change, the relative average wages in 2000 and 2016 for low-wage are higher and for high-wage occupations are lower, compared to the baseline economy. This result is surprising because these changes imply a relatively higher human capital for young workers in high-wage occupations. In this counterfactual the relative wages per unit of human capital for both occupations remains at similar levels to those in 1980, when that of high-wage was considerably higher than that of low-wage. As a result, the increase in the transferability of the human capital of young workers and the higher wages per unit of human capital in high-wage attracts a significantly higher share of workers, which decreases the average comparative advantage of young workers and leads to a lower average human capital. The opposite occurs in low-wage occupations.

In the third counterfactual, where I consider the changes in the variables that directly affect the mobility of workers, in 2000 the wage of high-wage is similar to that of the baseline economy in that year and that of low-wage is lower. For high-wage occupations the average relative human capital in steady-state decreases compared to the baseline because human capital growth and the human capital of young workers is lower, but this is almost entirely offset by higher unit wages, as the relative total human capital of these occupations is lower in steady-state. In the case of low-wage occupations higher mobility still has a positive effect on human capital accumulation so the human capital in steady-state is slightly higher than in the baseline, but without RBTC the unit wage increases less. On the contrary, in 2016 the average wage in low-wage occupations is higher and in high-wage occupations is lower than in the baseline. In high wage occupations, similarly to the baseline economy, lower mobility relatively increases human capital accumulation, which leads to a higher relative supply of human capital and pushes their unit wage downwards. The difference with the baseline economy is that the negative effect on unit wages is now higher because without RBTC there is no increase in the relative demand for the labor input of these occupations. For low-wage occupations the average human capital is higher than in the baseline economy because the human capital of young workers is more transferable and this compensates the lower unit wage in the absence of RBTC.

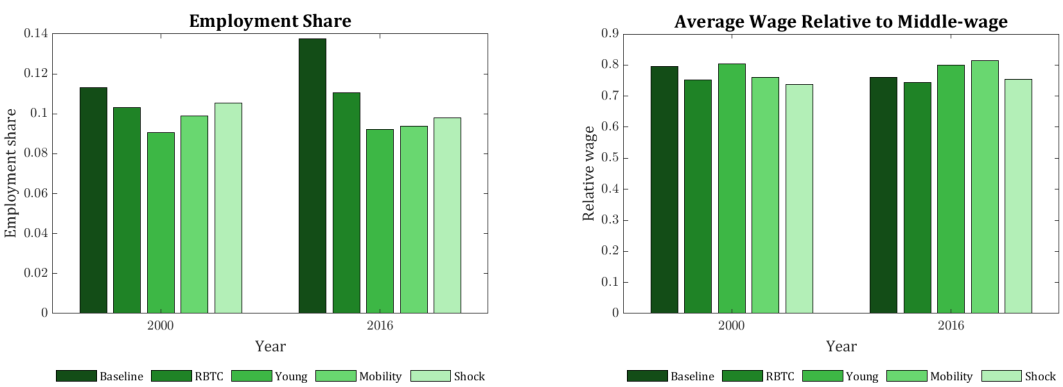
Finally, the last counterfactual allows for changes in the distribution of the productivity shocks of each occupation over time. The distribution of productivity shocks for low- and middle-wage occupations was relatively stable whereas for high-wage occupations the average productivity shock increased during 1980–2000 and decreased during 2000–2016 but remained above the 1980 value. Figure 13 shows that in this counterfctual in 2000 the average relative wage in high-wage occupations is higher than in the baseline economy due to more human capital accumulation thanks to lower occupational mobility. In 2016 the average relative wage of these occupations was lower than in the baseline because the decrease in the average productivity shock now it is not compensated with an increase in the average human capital of young workers. For low-wage occupations the average relative wage was lower than in the baseline economy both in 2000 and 2016 because when I shut down RBTC and the decrease in the human capital of young workers there is an excess of relative supply of human capital that lowers the relative unit wage.

Figure 13: Counterfactual Exercises. Years 2000 and 2016

(a) High-wage



(b) Low-wage



Notes: the figure plots employment shares and average wages relative to middle-wage occupations for high-wage -on the top panel- and low-wage occupations -on the bottom panel- in the baseline scenario discussed in Section 5 and four counterfactuals, in the years 2000 and 2016. The first column of each graph-year combination shows wages and employment shares in the baseline scenario and the remaining four columns show the changes in the same variables for counterfactual scenarios in which only the following parameters change according to the estimated parameters in Table 10: (i) occupation-biased technical change (A_j/A_i), (ii) transferability of the human capital of young workers (τ_j^0) and their non-pecuniary costs (χ_j^0), (iii) transferability of the human capital of older workers (τ_{jk}) and their non-pecuniary costs (χ_{jj}), (iv) productivity shocks (λ_j).

7 Conclusion

I document that during 2000–2016 the polarization of wages in the U.S. labor market ended, as the wage of low-wage occupations decreased relative to that of middle-wage occupations, while the polarization of employment continued during this period. These facts cannot be accounted for by routine-biased technical alone because it implies the substitution of routine tasks performed by workers in middle-wage occupations and an increase in the demand of non-routine low-wage and high-wage occupations.

To understand the end of wage polarization I present three motivating facts related to the level of occupational human capital. First, young workers increasingly work in low-wage occupations. Second, wages grow less with age in low-wage occupations than in the other occupations. Third, occupation mobility was lower during 2000–2016. In light of this evidence I develop a general equilibrium model to quantify the importance of routine-biased technical change and changes in occupational human capital on the onset and on the end of wage polarization. The key features of this model are occupation-biased technical change, human capital accumulation and occupational mobility. The model takes into account heterogeneity in the accumulation of human capital of workers in different occupations and that only part of their human capital is transferable across occupations.

I find that during 2000–2016 routine biased technical change continued pushing the relative wage of low-wage occupations upwards but human capital accumulation and occupational mobility changed and led to the end of wage polarization. Compared to middle-wage, workers in low-wage occupations accumulated less human capital and young workers in these occupations, who represented a relatively higher share of employment than before, had lower human capital. During 1980–2000 the changes in human capital accumulation of the occupations were similar to those during 2000–2016 but in the latter period these changes were amplified by less occupational mobility. This fall in occupational mobility decreases human capital accumulation in low-wage because more workers stay longer periods in these occupations with low human capital growth and fewer workers with higher human capital transition from middle- and high-wage occupations. The consistent increase in the relative wage of high-wage during 1980–2016 was due to an increase in the human capital of young workers that sort into these occupations and high human capital accumulation.

I perform counterfactual exercises to identify the effect of each of the forces in the model on employment shares and average wages. I show that routine-biased technical change was the main driver of the polarization of employment but the evolution of wages can only be understood by considering the interaction of all the forces in the model.

These results have significant implications for the growing wage inequality in the U.S. during the last four decades. The polarization of wages during 1980–2000 decreased inequality in the lower half of the wage distribution but the decrease in the relative wage of low-wage occupations during 2000–2016 reversed this trend. The results in this paper show that the changes in the accumulation of occupational human capital and lower occupational mobility led to higher wage inequality during 2000–2016. Moreover, this is exacerbated by the polarization of employment that increases the dispersion of wages due to the reallocation of workers to the occupations in the extremes of the wage distribution. If mobility does not change and the trends that I identify continue, inequality is likely to increase further.

An important extension of the analysis in this paper, that I plan to address in the future, is considering the transition dynamics between the years 1980, 2000 and 2016. Moreover, taking into account the heterogeneity in terms of demographic groups –e.g. gender, age– could be important to identify if the behavior of certain workers explain the changes identify in the parameters of the model across time. A possible direction for future research is exploring the forces behind the important changes that I identify in the human capital of young workers who sort in each of the occupations. Specifically, incorporating the accumulation of human capital through formal education together with the decision to enter the labor market are likely to have important implications as the share of workers with at least some college education increased significantly and the wages of these workers evolved differently in each occupation during 1980–2016. Another interesting avenue for future research is identifying the factors that increased the non-pecuniary costs of switching occupations during 2000–2016.

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Appendices

A Data Sources

A.1 Census and American Community Survey

Workers in the Census and ACS samples samples are asked about their current occupation. I do not consider residents of institutional group quarters -e.g. prisons and psychiatric institutions-, self-employed and unpaid family workers.

For the Census and ACS sample I measure labor earnings with the variable *incwage*, which reports each the worker's pre-tax wage and salary income and includes commissions, cash bonuses, tips, and other money income received from an employer but excludes payments-in-kind or reimbursements for business expenses. In the Census workers were asked about their income during the previous year whereas in the ACS the reference period are the previous twelve months. Hourly wages are computed as the yearly wage and salary income reported in *incwage* divided by the product of weeks worked during the last year and usual hours worked in a week. Because in the ACS annual weeks worked are only available in intervals, I assign workers weeks worked from the average of their one-digit occupational category using in a CPS sample with the same sampling criteria than my main sample. For the 1980 Census I substitute topcoded labor earnings values by 1.5 times the topcode and for the Census 2000 and ACS 2014-2018 5-year sample I replace the topcoded values with the average above the topcoded income by state.[36] I drop workers who earn less than half the minimum Federal wage in each of the reference years.

A.2 Panel Study of Income Dynamics

As in the Census, workers in the PSID are asked about their current occupation and their labor earnings during the previous year. To construct the sample to measure occupational mobility I select all the heads of household that were interviewed at time t and $t+2$ and satisfy the sampling criteria in both years.

For the calculation of the earnings transitions between occupations I measure annual labor earnings considering wages and salaries, any separate reports of bonuses, overtime, tips, commissions,

[36] For more information about topcoded values see https://usa.ipums.org/usa/volii/top_bottom_codes.shtml.

professional practice or trade, additional job income, and miscellaneous labor income. I calculate the workers' hourly wage by diving their annual earnings by their total annual hours worked. I drop workers workers with earnings higher that one million dollars and those who earn less than half the minimum wage in each year.

A.3 Robustness of Facts

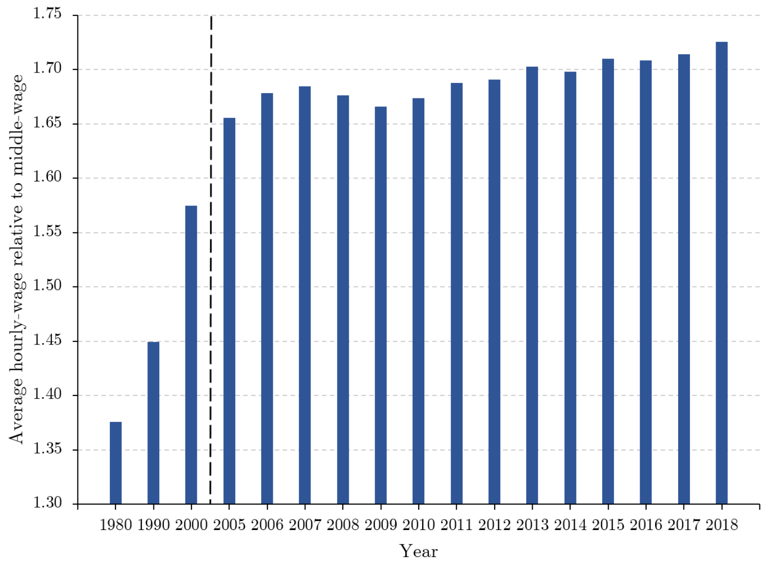
Table 8: Employment Shares and Log-hourly Wages by Broad Occupational Groups. Full-time and Part-time Workers. Years 1980, 2000 and 2016

	Employment share			Log-hourly wage		
	Level	Δ		Level	Δ	
	1980	80-00	00-16	1980	80-00	00-16
High-wage	27.0%	6.8%	5.2%	3.08	18.7%	8.6%
Middle-wage	61.8%	-8.6%	-7.8%	2.78	4.4%	-0.2%
Low-wage	11.2%	1.7%	2.6%	2.47	9.0%	-1.8%

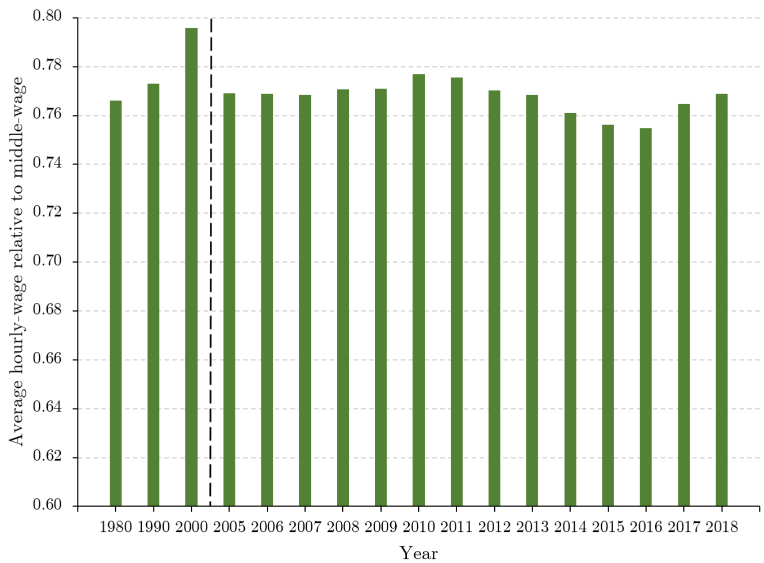
Notes: The sample includes workers that report strictly positive hours and weeks worked and satisfy all the other sampling requirements stated in Section 2.1. All workers are weighted by the product of their weeks worked, hours worked and Census weight.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

Figure 14: Average Hourly-wage. Relative to Middle-wage Occupations. Years 1980, 1990, 2000 and 2005–2018

(a) High-wage



(b) Low-wage



Notes: the figure shows the average hourly wage for workers in high- and low-wage occupations –Panel 14a and 14b, respectively–, relative middle-wage occupations, in 1980, 1990, 2000, and annualy during 2005–2018.
Source: Census 1980, Census 2000, American Community Survey yearly sample 2005–2018.

A.4 Cumulative Probability Distribution (CDF) of Employment by Age

Figure 15: Cumulative Probability Distribution (CDF) of Employment by Age. Years 1980, 2000 and 2016

(a) 1980

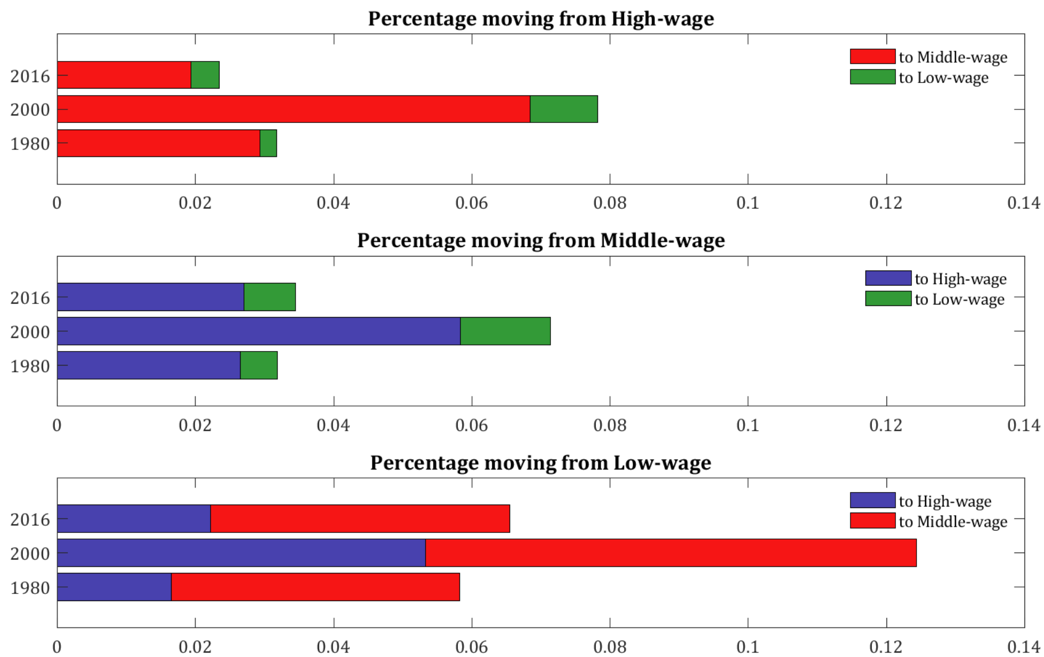
(b) 2000

(c) 2016

Notes: the figure shows the cumulative distribution (cdf) of employment by age for each of the broad occupational groups in the years 1980, 2000 and 2016.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample.

A.5 Disaggregated Mobility in 1980, 2000 and 2016

Figure 16: Mobility Across the Broad Occupational Groups.
Around the years 1980, 2000 and 2016



Notes: the figure shows annual mobility from each of the three broad occupational groups over six-year periods finishing in 1979, 1989 and 2017. To make the analysis comparable before and after 1997 -when the PSID started to conduct biennial surveys- I calculate occupational mobility as the fraction of workers who report a change in their occupational code between t and $t + 2$ and then calculate the implied yearly occupational mobility.
Source: Panel Study of Income Dynamics.

A.6 Targets and Model Predictions

Table 9: Data Targets and Model Predictions. Years 1980, 2000, 2016

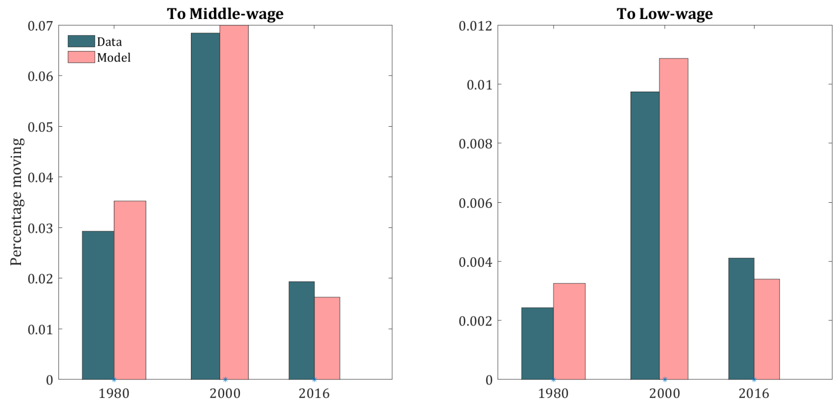
	1980		2000		2016	
	Data	Model	Data	Model	Data	Model
Average relative wage						
$\bar{w}_h/\bar{w}_m$	1.376	1.376	1.575	1.575	1.709	1.708
$\bar{w}_l/\bar{w}_m$	0.766	0.766	0.796	0.795	0.761	0.761
*Transition of earnings**						
$(w_m/w_h) * M_{hm}$	0.030	0.030	0.067	0.067	0.018	0.018
$(w_l/w_h) * M_{hl}$	0.003	0.003	0.010	0.010	0.004	0.004
$(w_h/w_m) * M_{mh}$	0.028	0.028	0.061	0.061	0.029	0.029
$(w_l/w_m) * M_{ml}$	0.005	0.005	0.012	0.012	0.008	0.008
$(w_h/w_l) * M_{lh}$	0.017	0.017	0.053	0.053	0.020	0.020
$(w_m/w_l) * M_{lm}$	0.044	0.044	0.075	0.075	0.041	0.041
Percentage of stayers						
μ_{hh}	0.968	0.961	0.922	0.919	0.977	0.980
μ_{mm}	0.968	0.973	0.929	0.935	0.966	0.968
μ_{ll}	0.942	0.951	0.876	0.891	0.935	0.946
Average relative wage 16–24						
$\bar{w}_h^0/\bar{w}_m^0$	1.108	1.106	1.274	1.276	1.383	1.384
$\bar{w}_l^0/w_m$	0.806	0.807	0.842	0.841	0.851	0.849
Employment shares 16–24						
θ_h^0	0.158	0.158	0.175	0.175	0.211	0.211
θ_l^0	0.105	0.105	0.175	0.175	0.236	0.237

Notes: the table reports the moments used to jointly calibrate the parameters described in Section 4 in 1980, 2000 and 2016.
*Normalized with respect to the average wage growth of workers staying in middle-wage occupations.
Source: Census 1980, Census 2000, American Community Survey 2014–2018 5-year sample, and Panel Study of Income Dynamics.

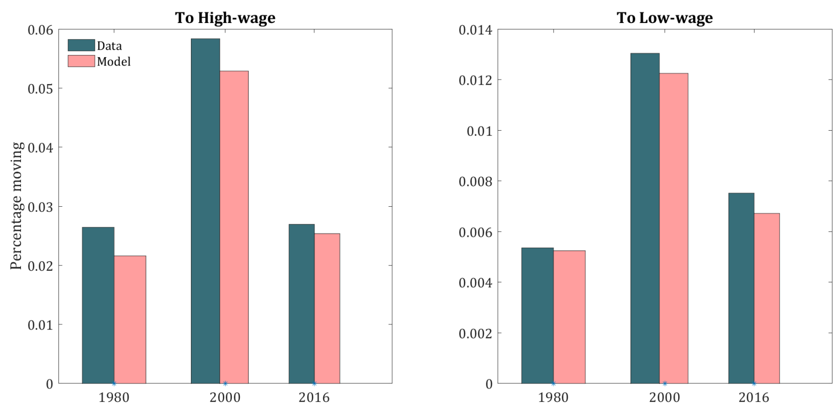
A.7 Data and Model Mobility

Figure 17: Data and Model Predicted Mobility. Years 1980, 2000, 2016

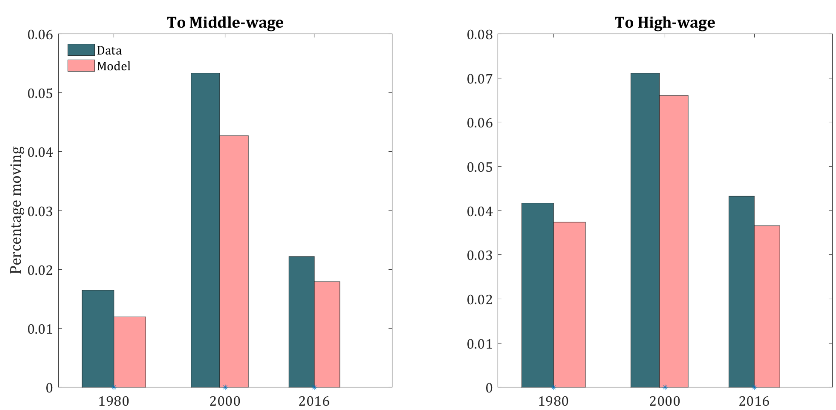
(a) From High-wage



(b) From Middle-wage



(c) From Low-wage



Notes: the figure compares the untargeted annual pairwise mobility across occupations from the PSID data to that in the economies calibrated in 1980, 2000 and 2016.
Source: Panel Study of Income Dynamics.

A.8 Calibrated Parameters

Table 10: Estimated Parameters.
Years 1980, 2000, 2016

	1980	2000	2016
Productivity shocks			
λ_h	0.954	0.979	0.969
λ_l	0.936	0.927	0.933
Transferability of HK			
τ_{hm}	0.641	0.633	0.661
τ_{hl}	0.762	0.675	0.693
τ_{mh}	1.110	1.119	1.037
τ_{ml}	1.055	0.921	0.907
τ_{lh}	0.799	0.909	0.864
τ_{lm}	0.666	0.745	0.748
Non-pecuniary costs			
χ_{hh}	0.921	0.990	0.906
χ_{mm}	0.882	0.942	0.889
χ_{ll}	0.840	0.917	0.880
Transferability of HK, young			
τ_h^0	1.054	1.286	1.534
τ_l^0	1.168	1.021	0.927
Non-pecuniary costs, young			
χ_h^0	0.904	1.087	1.354
χ_l^0	0.972	0.928	0.836

Notes: the table reports the value of the parameters jointly calibrated by matching the moments in 1980, 2000 and 2016, as described in Section 4.