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IS EMPLOYMENT POLARIZATION INFORMATIVE ABOUT WAGE INEQUALITY AND IS EMPLOYMENT REALLY POLARIZING?

Jennifer Hunt
Ryan Nunn

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Cambridge, MA 02138
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ABSTRACT

Equating a job with an individual rather than an occupation, we re-examine whether U.S. workers are increasingly concentrated in low and high-wage jobs relative to middle-wage jobs, a phenomenon known as employment polarization. By assigning workers in the CPS to real hourly wage bins with time-invariant thresholds and tracking over time the shares of workers in each, we do find a decline since 1973 in the share of workers earning middle wages. However, we find that a strong increase in the share of workers in the top bin is accompanied by a slight decline in the share in the bottom bin, inconsistent with employment polarization. Turning to occupation-based analysis, we show that the share of employment in low-wage occupations is trending up only from 2002-2012, and that the apparent earlier growth and therefore polarization found in the literature is an artefact of occupation code redefinitions. This new timing rules out the hypothesis that computerization and automation lie behind both rising wage inequality and occupation-based employment polarization in the United States.

Jennifer Hunt
Department of Economics
Rutgers University
New Jersey Hall
75 Hamilton Street
New Brunswick, NJ 08901-1248
and IZA, CEPR, DIW-Berlin
and also NBER
Jennifer.hunt@rutgers.edu

Ryan Nunn
Brookings Institution
1775 Massachusetts Ave. NW
Washington, DC 20036
rnunn@brookings.edu

1 Introduction

A decline in the middle class has become a concern not only in the United States, but also in other countries, and not only for academics, but also for politicians and the public.[1] Economists and sociologists who study the declining share of workers earning middle wages are in some cases motivated by apprehension that it implies falling worker welfare, and in other cases by an interest in the possible implications for other labor market phenomena such as changing work tasks and rising wage inequality. To answer any of these questions, it is crucial to understand whether workers earning middle wages are instead earning higher wages, lower wages, or some mix of the two (what one might loosely call "polarization").

In this paper, we test for polarization of U.S. wages using three approaches, providing insights into changing worker welfare and an assessment of whether these approaches are informative for evaluating theories of rising wage inequality. In doing so, we critique an existing literature which finds polarization, but more importantly, we caution against over–generalizations made by many readers of this literature.

The influential existing approach has focused on employment growth at the occupation level. To this way of thinking, occupations serve several purposes: their average wages stand in for either job quality or skill and their other characteristics convey information about the nature of work. Many economists have found occupation–based employment polarization—employment growth in high and low–paid occupations and relative decline in middle-paid occupations—in the United States and other countries;[2] only two studies of the United States dissent.[3] Sociologists, on the other hand, have found mixed evidence for polarization in countries outside the United States, sometimes contesting the results of studies by economists. Expansion in the share of high–wage occupations is found in all high–income countries, but while in some countries a rising share of employment in

[1] See for example Fukuyama (2012); New York Times (2015); Bloomberg (2016); Le Figaro (2016) citing the International Labour Office (n.d.) study of Europe; Pew Research Center (2016); Financial Times (2019) citing OECD (2019).

[2] Levy and Murnane (1992); Acemoğlu (1999); Autor, Levy and Murnane (2003); Goos and Manning (2007); Autor, Katz and Kearney (2008); Spitz–Oener (2008); Goos, Manning and Salomons (2009); Autor (2010); Acemoğlu and Autor (2011); Kampelmann and Rycx (2011); Autor and Dorn (2013); Goos, Manning and Salomons (2014); Autor (2015a,b); Coelli and Borland (2016); Foote and Ryan (2015); Green and Sand (2015); Harrigan, Reshef and Toubal (2016); Cerina, Moro and Rendall (2017); Bárány and Siegel (2018); Autor (2019). See also the study by sociologists Wright and Dwyer (2003). Firpo, Fortin and Lemieux (2013) link tasks to wage inequality.

[3] Lefter and Sand (2011); Mishel, Shierholz and Schmitt (2013).

low–wage occupations and a falling middle share together indicate polarization, sociologists classify other countries as experiencing occupational upgrading due to their falling employment share of low–wage occupations.[4]

While employment polarization is analyzed in some studies for its own sake or principally to understand the evolution of tasks performed by workers, most research by economists sets employment polarization in the context of rising wage inequality, and some researchers directly investigate a possible connection with rising wage inequality. Figure 1 shows that while the difference between log wages at the 90th percentile and the median has been growing steadily since 1973, trends in the lower part of the distribution have been less simple. The difference between the median and the 10th percentile rose considerably in the 1980s, but has since stabilized at a level slightly below its 1987 peak. Acemoğlu and Autor (2011) introduce a theoretical model to explain both this particular pattern and employment polarization[5]; less formal discussions of the theory appear in Autor (2015a,b). A common element of these accounts is that investments in computerization and automation are complementary with workers in high–skill occupations and raise their labor demand and wage, while reducing demand and wages for workers in middle–skill occupations through the elimination of routine tasks, and increasing the supply of workers in low–pay occupations as middle–skill workers crowd in to those occupations. We believe the theory implies that the share of workers in low–wage occupations should rise, ceteris paribus. Other researchers have understood polarization to require only that the middle–wage occupation share have lower growth than the low and high–wage occupation shares, and this distinction between an absolute and a relative understanding of polarization will sometimes be important for interpreting our results.

The theory does not unambiguously imply that employment polarization would lead to the wage inequality patterns seen since 1990, in particular the stability or decline in the 50/10 wage differential. On the one hand, the displacement of workers from middle–wage occupations to low–wage occupations increases supply of low–wage workers; on the other hand, demand for low–wage services may rise with the rising numbers of the high–wage workers. Together, these shifts imply increased low–wage employment but

[4] Oesch and Menes (2011); Oesch (2013); Murphy and Oesch (2018); Fernandez–Macias (2012); Hurley and Fernandez–Macias (2008).

[5] "Thus the introduction of new machines replacing middle skilled tasks in this framework provides a possible formalization of the "routinization" hypothesis and a possible explanation for job and wage polarization discussed in Section 2." (p.1141)

have ambiguous implications for wages. Nevertheless, early writing on U.S. polarization[6] has been understood by many readers to imply that employment polarization provides empirical support for a link between computerization and wage inequality,[7] even though the later literature is more circumspect.[8]

However, the limitations of the occupation–based approach to job quality and wage inequality are not widely appreciated. While occupations may provide reliable information about tasks and the nature of work at a point in time, average occupation wages are in general not appropriate proxies for individual wages, nor is the distribution of occupations by average wage very informative about the distribution of workers' wages. This is most immediately evident in the large amount of wage dispersion that exists within detailed occupations, as emphasized by Mishel, Shierholz and Schmitt (2013). Even more importantly, 86% of the increase in wage inequality from 1973–2018 is within detailed occupations, as measured using the variance of log hourly wages in our sample from the U.S. Current Population Survey (CPS).

The weak mapping between occupation average wages and individual wage percentiles is made clear by the striking observation that in the 1983 CPS, only the three lowest paid of 330 detailed occupations have mean wages at or below the 10th percentile of individual wages, and only the five lowest paid have mean wages below the 20th percentile. Furthermore, middle–wage workers are spread very evenly across occupations ranked by mean wage. Mean wages of occupations are therefore unhelpful for understanding changes in wage inequality.

We therefore turn to an approach to testing for employment polarization based on

[6] For example, referring to the 1988–2006 period, Autor (2010, p.3) writes, "Wages both above and below the median rose relative to the median. [...] This simultaneous polarization of U.S. employment and wage growth suggests an important theme, explored in detail below – labor demand appears to be rising for both high–skill, high–wage jobs and for traditionally low–skill, low–wage jobs." Autor and Dorn write, "So computerization is not reducing the quantity of jobs, but rather degrading the quality of jobs for a significant subset of workers. Demand for highly educated workers who excel in abstract tasks is robust, but the middle of the labor market, where the routine task-intensive jobs lie, is sagging. Workers without college education therefore concentrate in manual task-intensive jobs like food services, cleaning and security which are numerous but offer low wages, precarious job security and few prospects for upward mobility. This bifurcation of job opportunities has contributed to the historic rise in income inequality." https://opinionator.blogs.nytimes.com/2013/08/24/how-technology-wrecks-the-middle-class, accessed July 2, 2019.

[7] See the literature reviews in Lacuesta and Izquierdo (2012), Oreopoulos and Petronijevic (2013), Green and Sand (2015), and Cortes (2016).

[8] For example, Autor (2015b) states that "Thus, while computerization has strongly contributed to employment polarization, we would not generally expect these employment changes to culminate in wage polarization except in tight labor markets" (p.146).

individual rather than occupation wages. We revive and improve a method fallen into disuse, assigning workers to real hourly wage bins with time-invariant thresholds and tracking over time the shares of workers in each.[9] Employment polarization would constitute a fall in the share in the middle wage bins and a rise in the share of workers in the bottom as well as the top wage bin. We conduct our analysis for 1973–2018 using CPS Merged Outgoing Rotation Group (MORG) and May samples. Our use of annual data allows us to distinguish trends and business cycles and to capture accurately the timing of longer-term patterns, unlike most of the previous literature which uses decadal census data for years until 2000.

We use the wage–bin approach in part because many readers appear to think this method is equivalent to the prevailing occupation–based approach, or think it delivers similar results.[10] However, this is not the case. Over particular time periods, employment growth can and does occur disproportionately in high–wage jobs within low–wage occupations, or low–wage jobs within high–wage occupations. In addition, inconsistencies between the occupation and wage approaches could arise because harmonization of changing occupation codes is necessarily imperfect, particularly over long periods of time. Indeed, occupation codes change because the nature of occupations changes over time, including through upskilling.[11]

Grouping workers into four time–invariant bins defined only by workers' wages, we do find a steady decline in the share of workers in the middle two wage groups, but one that belies offsetting forces that vary over time and by gender, variously reflecting either upward mobility (workers moving faster from the middle to the top than from the bottom to the middle) or downward mobility (workers moving faster from the middle to the bottom than from the top to the middle), but not employment polarization. The business cycle clearly has a tendency to cause downward mobility in recessions and upward

[9] Bluestone and Harrison (1988); Levy and Murnane (1992); also LoPalo and Orrenius (2015). Gittleman and Howell (1995) do similar analysis based on a multidimensional measure of job quality.

[10] For example, Haskel at al. (2012) write without mentioning occupations: "The result is downward pressure on wages and employment opportunities on moderately skilled workers, such that inequality between them and their less–skilled counterparts no longer rises. Autor (2010b) discusses this 'polarization' of the U.S. labor market." Canon and Marifian (2013) write without mentioning occupations: "...the economy has increased its demand for high-skilled (high–wage) workers and low–skilled (low–wage) workers, while opportunities for middle–skilled (middle–wage) jobs have declined. The shift toward this U–shaped employment distribution is known as job polarization."

[11] See Levy, Murnane and Tyler (1995), and Spitz-Oener (2006) for Germany. In their analysis of wage inequality, Gottschalk, Green and Sand (n.d.) grapple with the issue of the changing skills associated with occupations.

mobility in recoveries and booms.[12] However, the shares of workers in the top and bottom groups generally move in opposite directions over the longer term as well, with the share in the top group rising markedly and the share in the bottom falling slightly. The patterns are very similar with ten wage bins rather than four.

Long–run trends are very different by gender. After adjusting for the business cycle, we see that women have experienced upward mobility since 1982, with the share in the bottom wage group falling considerably, the middle two groups falling slightly, and the top wage group rising considerably. The decline in the middle is thus a positive development for female workers, reflecting both welfare improvements for individuals and composition changes generated by the 1980s surge in labor force participation. Men experienced strong downward mobility in the 1980s as the shares of the upper two wage groups both shrank. However, men experienced mild upward mobility from 1992–2003, with a small increase in the share in the top wage group at the expense of middle groups, and have experienced little change since. The decline in the middle for men was thus deleterious in the 1980s and beneficial in the later period.

To understand these trends better, we perform Oaxaca decompositions of changes in the shares of workers in wage bins over time. This allows us to search for any polarizing factor that might be obscured by rising age and education and to examine the effect of the changing composition of occupations. An alternative to investigating whether generally improving worker–level variables are obscuring polarization is to use a measure of polarization that is invariant to changes in the median wage. While such a measure could be constructed within a wage–bin framework, we instead supplement our wage–bin analysis with the Foster and Wolfson (2009) test for polarization based on changes in the distance of workers' wages from the median.

Our Oaxaca decompositions of year–to–year changes in wage bin shares do not identify any polarizing factor for either men or women, nor is polarization uncovered when age and education are held fixed over time. Furthermore, the decompositions (using either four or ten wage bins) show that changes in occupation mix have worked towards reducing the share of women in the bottom bin until 2001, with no subsequent effect, while having little effect on the share of men in the bottom bin. Similarly, the Foster and Wolfson test for polarization of the "increased spread" type shows that while above–median wages have

[12] This is notwithstanding the fact that unskilled workers disproportionately exit employment in recessions and disproportionately enter employment in booms.

been moving away from the median almost throughout the study period, below–median wages have by comparison been almost stationary compared to the median.

The slight downward trend in the share of workers with low wages could in principle coexist with a growing employment share of low–wage occupations, growth which is predicted by the computerization and automation polarization theory and is found in the U.S. empirical literature from 1989. We show that the share of low–wage workers in occupations with low mean wages falls greatly with time, a factor which could be outweighing an expanding employment share of low–wage occupations. However, we also show that the share of employment in low–wage occupations is trending up only from 2002–2012, and that the apparent earlier growth found in the literature is an artefact of an unbridgeable change in occupation codes in 2000. The pattern does not change when we focus on the service occupations at the heart of the Autor and Dorn (2013) investigation of rising employment in low–wage occupations. Furthermore, adding agricultural occupations to the occupations studied in the U.S. literature yields a falling employment share of low–wage occupations prior to 2000. The implied lack of occupation–based employment polarization prior to 2002 once the occupation code break is taken into account is consistent with the findings of Lefter and Sand (2011) and Mishel, Shierholz and Schmitt (2013).

The employment share of non–college workers in low–wage occupations is shrinking throughout the 1973–2018 period and therefore does not contribute to growth in the low–wage occupation share (and consequently to overall polarization). However, as noted by Autor (2019), the share of non–college workers in low–wage occupations as a share of non–college employment is rising: viewed in isolation, non–college workers are polarizing. This hints at the possibility that underlying occupation–based employment polarization is masked by human capital–driven occupational upgrading of workers (see Murphy and Oesch 2018), something difficult to test. Barring a concealed polarization of this nature, the late (post-2000) emergence of occupation–based polarization means it cannot be explained by computerization and automation, as hypothesized in the literature, nor linked to rising wage inequality. Computerization and automation, and indeed offshoring and increased trade, began well before 2002, as did the rise in wage inequality.

Computerization and automation may be increasing wage inequality, but the hypothesis cannot be studied through the lens of occupations and does not find support in the study of employment polarization, however defined.

2 Data

We use the merged outgoing rotation groups (MORGs) from the Current Population Surveys (CPS) of 1979–2018 and the smaller May CPS samples from 1973–1979. We retain imputed values following Card and DiNardo (2002), though this could affect the estimated changes in return to union status (Hirsch and Macpherson 2003). We draw a sample of workers aged 18–64 who are not self-employed, and compute hourly wages by dividing weekly earnings by usual weekly hours; from 1994 we use hours worked last week on all jobs where usual hours on the main job are reported to be variable. We adjust wages to represent 2018 dollars by deflating with the CPI-U-RS (real wages grow slightly more slowly using the CPI-U, but results are very similar); topcoded earnings are multiplied by 1.5. We drop wages below \$2 in 2018 dollars or above \$200 if usual weekly hours are less than or equal to 15. We also drop workers with missing observations on age, education, industry, occupation or state. For the Oaxaca decomposition only, which we perform for 1983–2018, we also drop workers with missing information on union status: since union information is not available in all years prior to 1983, dropping these observations would result in breaks in the series. The means of the main Oaxaca covariates for women and men in selected years are given in Appendix Tables 1 and 2 (the Data Appendix explains how we generated 34 harmonized industry codes).

Because the heaping of wages at round numbers would otherwise cause sudden jumps over time in the shares of workers in wage bins, we add some randomness to each wage. We draw a random value k_i from a standard normal distribution and multiply the wage by $0.2k_i$, or equivalently, add $0.2k_i$ to the log wage. This acts to smooth the wage distribution by dispersing the heaps of workers who report particular round–number nominal wages like \$10 per hour or \$15 per hour. Without this randomness, inflation—combined with the clustering of workers at fixed nominal wages—causes frequent discontinuous shifts in employment shares.[13]

Certain data issues will become salient below. One is independent of the specific data set: occupation codes are redefined by the Census Bureau every ten years at the time of the decennial census. For consistency with virtually the entire U.S. employment polarization literature, we use the 330 detailed harmonized occupations on David Dorn's

[13] We have experimented with the amount of randomness to be added, and found $0.2k_i$ to be the smallest amount that serves to prevent the discontinuous shifts. Previous authors using wage bins did not adjust for heaping. We have redrawn from the distribution each time we have updated the CPS MORGs and have not found the results to be sensitive.

website[14] (though using updated codes kindly provided to us by Brad Hershbein and Elisa Jacome for the years after 2010). However, the new codes of 1980 and 2000 constituted such large breaks that even the Dorn harmonized codes leave large jumps in employment for many occupations across these two code breaks. The 1980 codes were introduced to the CPS in 1983, while for 2000–2002, occupations were coded in the CPS using both the 1990 and the 2000 codes. We take advantage of this overlap to extend the periods that can be examined without a code break, and to correct jumps in employment shares: we do not use the improved harmonizations proposed by Lefter and Sand (2011) and Shim and Yang (2018).[15]

Two further issues are specific to the CPS. The 1994 redesign resulted in workers being shifted to better–paying occupations (Cohany et al. 1994), which means that analysis using occupations in the CPS will have a break in 1993–1994. Furthermore, until 1989, CPS earnings do not include tips, overtime and bonuses. Among bottom occupations, this particularly affects waiters and waitresses, who prior to 1989 have the lowest hourly wages in the CPS, but rank considerably higher beginning in 1989.

3 Methods

We employ three methodological approaches. The first is to assign workers to real wage bins and calculate employment shares based only on individual wages, with no use made of occupations or their average wages. We augment this approach by adjusting for the business cycle and by performing Oaxaca decompositions of the changes in shares of workers in each wage bin over time. The second approach follows Foster and Wolfson (2009) but continues to use individual wages as the unit of analysis. The third approach is to categorize workers based on the average wages of their occupations. In most of the latter analysis, we adopt the methods of the existing polarization literature.

[14] https://www.ddorn.net/data.htm, accessed 31 October 2018.

[15] The aggregate codes, sometimes used in the U.S. polarization literature in addition to the detailed codes, were changed in 2000 to reflect a new approach: "The major occupational groups of the new SOC and the derivative 2002 Census Bureau occupational classification place more emphasis on the type of work performed and less emphasis on skill or educational level" (Bowler et al. 2003).

3.1 Defining wage bins

We allocate each worker in each year to one of four wage bins, whose thresholds are constant in real terms over time. We choose the thresholds that divide workers into quartiles in 1979: in years other than 1979, shares sum to one but are not necessarily equal. The same bins are used whether men and women are pooled or examined separately. Workers in the bottom wage bin earn $11.71 per hour or less (in 2018 dollars), workers in the lower middle group earn more than $11.71 and less than or equal to $17.05, workers in the upper middle group earn between $17.05 and $25.25, while workers in the top group earn more than $25.25. We show some results using ten groups based on 1979 deciles rather than quartiles (workers earn $8.90 or less in the bottom bin and more than $35.08 in the top bin); unreported results using four groups based on 2007 quartiles yielded similar results. The May samples and the MORG samples overlap for the years 1979–1982, yielding similar but not identical shares of workers in bins in those years. We therefore normalize the May shares to be equal to the MORG shares in 1979.

3.2 Adjusting for the business cycle

The evolution of employment shares is affected by the business cycle in a way that could obscure longer-run patterns. We therefore adjust time series for shares in each wage group for the business cycle in several steps. We first regress each time series of 46 observations on two lags of the unemployment rate, using a linear probability model. We then compute the residuals and predict what the shares would have been in each year had the lagged unemployment rates been at their 1979 values.

3.3 Oaxaca-Blinder decompositions

We perform Oaxaca-Blinder decompositions of the changes in shares of workers in bins over time, based on linear regressions of the probability of a worker being in a given bin in a given year. This informs us as to the role in any period of changing worker characteristics compared to changing returns to characteristics. The base year is the earlier of the pair of years. We use the Oaxaca command in Stata from Jann (2008), which permits the contributions of individual covariates and their coefficients (returns) to be computed. However, there is disagreement on how to calculate the contributions of the individual coefficients, with Firpo, Fortin and Lemieux (2011) preferring a different method from Jann (2008). Given the lack of consensus, we do not report this part of the decomposition. In the baseline case of four wage bins, we implement linear regressions of the form

$$Y_t^k = X_t' \beta_t^k + \epsilon_t, \; k \in \{1,2,3,4\}, \, t \in \{0,1\}$$

where Y_t^k is the employment share in bin k and year t, X_t is a vector of covariates in year t, and ϵ_t is the error term. We then compute the terms in the following equation:

$$\begin{aligned} E(Y_{t=1}^k) - E(Y_{t=0}^k) = & \underbrace{[E(X_{t=1}) - E(X_{t=0})]' \beta_{t=1}^k}_{\text{Changes in covariates across years}} \\ & + \underbrace{E(X_{t=0})'(\beta_{t=1}^k - \beta_{t=0}^k)}_{\text{Changes in returns to covariates}}, \; k \in 1,2,3,4. \end{aligned}$$

For the decompositions, we use the MORGs beginning in 1983, the first year in which union information (important for men) is included in the MORGs (this fortuitously also allows us to avoid the occupation code break across 1982–1983). We present tables with decompositions (with standard errors) for 1983–1990, 1990–2008, and 2008–2018. We select 1990, 2008 and 2018 because the position in the business cycle is similar at these points.[16] The results of the decomposition are affected by selection—into and out of the labor force, and into and out of union membership, for example—and the estimated returns are not necessarily causal. We include all characteristics including occupation dummies. This has the advantage that the role of the changing occupational distribution may be assessed in the light of the occupation–based literature. The disadvantage is that for women particularly, movement to better–paying occupations is an outcome of interest in its own right. We therefore also present decompositions without occupation.[17]

We also construct graphs (without standard errors) based on Oaxaca decompositions of changes in wage group shares between each adjacent pair of years for 1983–2018. These adjacent–year plots allow a finer appreciation of the timing of various effects than do the decompositions over longer periods. The main aim is to show how the share of workers in a group would have evolved yearly from 1983 had only a single covariate evolved, with all others held constant. For example, to show the effect of changing education, we plot

[16] The decomposition using the 1980 May and the 1990 MORG is available on request.
[17] Since country of birth is available only from 1994, we defer the study of immigration's role to further research.

the 1983 predicted share for 1983, then add the contribution of changing education to the 1983–1984 change in group share and plot this for 1984, then add to this 1984 value the contribution of changing education to the 1984–1985 change in group share and plot this for 1985, and so on.

3.4 Foster–Wolfson measure of polarization

Foster and Wolfson (2009) propose a test of whether a distribution is polarizing in a manner they call "increased spread". For each distribution of interest, the values (here, wages) are first normalized by the median value, then the absolute value of the distance of each wage from the median is calculated. Formally, a Foster-Wolfson curve is defined by

$$S_t(q) = \frac{|F_t^{-1}(q) - F_t^{-1}(0.5)|}{F_t(0.5)},$$

where F_t is the cumulative distribution function of wages in year t.

To compare an earlier and a later distribution, the mean distances for each normalized wage percentile are plotted against the percentiles, with polarization occurring if the later distribution lies above the earlier distribution both to the left and the right of the normalized median wage. This would imply that below–median wages are falling farther from the median, while above–median wages are rising farther from the median.

3.5 Assessment of occupation–based employment polarization

To study employment changes by occupation, we follow the literature by dropping agricultural occupations (though we test sensitivity to this), and we rank the remaining 323 occupations by mean wage.[18] Papers such as Autor and Dorn (2013) rank occupations based on the 1979 wage from the 1980 census. So as to rank based on the same occupation codes, we rank based on 1983 wages. Because the literature including Autor and Dorn (2013) weights hourly wages with annual hours, we weight with usual weekly hours (annual hours are not available in the CPS MORGs and Mays), thus ranking occupations by their wage bill divided by their total hours worked.

[18] Autor and Dorn (2013) state they use 318 occupations. We are unsure which further occupations they drop if any.

In our simplest analysis, we plot the employment share over time of the lowest-paid occupations, defined as those that cumulatively (based on the wage rankings) employ 10% of workers in 1983. We plot this employment share because of the focus on the 10th percentile wage in the wage inequality literature and also because the presence or absence of polarization in the existing literature hinges on whether the share of this group is rising or not, given the employment shares of high–wage occupations and middle–wage occupations have clearly been rising and falling, respectively. In all rankings, the large occupation of health and nursing aides is the highest ranked occupation with at least some employment in the 10th occupation–based percentile. Since it is both rapidly growing and particularly affected by government policy, we show shares with and without this occupation.

To follow the literature and explore occupation–based polarization fully, we then reduce the 323 non–agricultural occupations to 100 "percentiles" each containing one percent of workers. Following the literature, this first entails ranking the occupations by average wage. Second, the lowest-wage occupation is apportioned to the lowest percentile bin. If that occupation falls short of one percent of total employment, then the second-lowest-wage occupation is added to the same bin; otherwise, the remaining employment share of the first occupation is apportioned to the second (and possibly subsequent) bins. This continues until the employment share of each occupation has been mapped to the 100 percentile bins. We calculate changes in employment share by "percentile" for various periods and estimate the relationship between the change in employment share and occupation rank using a lowess regression (with a bandwith of 0.75, as in Autor and Dorn 2013). The final plots are of this relationship. Employment changes in large occupations like secretaries and managers n.e.c. are divided among as many as four percentiles, and even small occupations may span two percentiles: this tends to smooth the employment changes by occupation.[19]

4 Is employment polarizing based on wage bins?

We begin the presentation of our results by assessing whether there is employment polarization in our wage–bin framework. Next, we perform Oaxaca decompositions to search

[19] Some papers using non–U.S. data have examined the more logical relationship between change in employment share and occupation average log wage rather than the rank (Goos and Manning 2007, Kampelmann and Rycx 2011). CPS results for the latter relationship are available from the authors.

for factors that might be tending to polarize employment even if offsetting other factors mean overall employment is not polarizing.

4.1 Wage bin analysis of pooled men and women

We depict in Figure 2 the shares of workers in each of the four wage groups from 1973–2018; by construction a quarter of workers are in each group in 1979. The graph shows a gradual decline in the share of the two middle groups, which is consistent with employment polarization. But in a departure from employment polarization, it does not show simultaneous increases in the top and bottom group shares. The share of workers in the top bin rises from 0.25 in 1979 (and a similar value in 1973) to 0.35 in 2018, while the share of workers in the bottom wage bin declines from 0.25 in 1979 (and a similar value in 1973) to an all–time low of 0.18 in 2018, after peaking at 0.30 in 1983–1985. The occupation–based literature generally weights workers by their annual hours; we can weight workers with their weekly hours and obtain a similar figure (Figure 3).[20]

Short–run changes in the shares in the top and bottom are related to the business cycle: during the recessions of the early 1980s and late 2000s, the share in the bottom group rises and the share in the top group falls, while the opposite occurs in the expansion periods, and especially during the boom of 1996–2001 and in the current expansion. Longer–run trends are somewhat clearer when employment shares are adjusted for the business cycle (Figure 4, not weighted by hours), though the adjustment is clearly not very successful in the 2000s. With this adjustment, the share in the top bin trends strongly and fairly steadily upwards over the 1973–2018 period. The share in the bottom bin ends the period well below its initial value, with much of the decline occurring during the 1990s expansion. The changes in top and bottom shares dwarf changes in the middle shares.

The patterns we find are not very sensitive to the choice of number of wage bins. Because workers are generally moving up through the wage bins rather than exhibiting polarization or another more complex pattern, changes in shares are concentrated in the top and bottom bins where inflows are not compensated by outflows or vice versa. Figure 5 shows that there is no long run polarization when using ten bins, though in this case there is less decline in the share in the bottom bin. However, since we scrutinize the period

[20] Our results differ from those of LoPalo and Orrenius (2015), who find a rise in the share in the bottom between the pair of years 1979 and 2012. However, after deheaping the data, the authors find results consistent with ours in the CPS using any deflator, and in the Census/ACS using any deflator other than the CPI-W (personal communication).

from 2002–2012 more carefully below, it is worth noting that with ten bins, the share in the top bin rises slightly over this period, which combined with the rise in the share of the bottom in this period (independent of the number of bins) means that there is slight employment polarization in these years. Some of the rise in the bottom in this period (and of the steep decline since 2014) is likely to be a business–cycle effect, but the weak recovery after the 2002 recession suggests a trend change.

It is possible that steadily rising age and education, by pushing workers into higher wage bins, is disguising underlying polarization within age–education cells. Accordingly, we simulate in Figure 6 the evolution of the four wage bin shares holding age and education fixed at their 1979 levels.[21] This analysis implies that had age and education not risen, the share of workers in the bottom bin would have risen considerably, while the share in the upper two bins would have fallen, with no sign of polarization.

The lack of polarization in our framework could be compatible with polarization in the occupation framework. An easy way to see this is to consider the share of low–wage occupation workers (employing 10% of workers, excluding health and nursing aides) who are in the bottom wage bin. The upper line in Figure 7 shows that while in the early 1970s almost 70% of low–wage occupation workers were in the bottom of our four wage bins, this had fallen to 50% by 2018 (the series has been adjusted for breaks in 1983, 1994 and 2002 as described below). The lower line shows that the share of low–wage occupation workers who are in the bottom of our ten wage bins peaked at 45% in 1988 and had fallen to little more than 20% by 2018. These low shares presage our concerns below about the mapping between occupation–based wage percentiles and individual–based wage percentiles, but the point here is that rising wages within occupations could allow low–wage occupations to expand even as the share of low–wage work declines.

4.2 Wage–bin analysis by gender

The patterns in the employment shares of workers shown in Figures 2–5 mask very different patterns for men and women. For women, the wage shares plotted in Figure 8 suggest that the principal development is that women are steadily moving up through the wage groups, which continue to be defined based on the pooled male and female sample (the series adjusted for the business cycle is in Figure A1). Figure 8 shows that until 2003, the

[21] This is a partial–equilibrium exercise that likely does not accurately capture the true counterfactual labor market with no change in age and education, but it may be illuminating nonetheless.

shares in the bottom and lower middle wage groups declined as the shares in the upper middle and top groups rose, implying women moved from the lower two groups to the upper two groups. However, female progress slowed from 2003, with a rise in the share in the bottom bin until 2012 implying employment polarization over this interval.

Men's patterns are quite different. In Figure 9, the effects of the business cycle on the shares in the top and bottom wage groups are more marked than for women. The share in the upper middle bin fell from 1973 through the early 2010s with little change in the share in the lower middle. There appear to be three distinct periods for men based on trends in the top and bottom shares: the 1980s, when men slid down through the wage groups; 1992–2003, when there was a partial recovery with upward mobility through the groups; and the period since 2003, with relatively little movement (see also the business–cycle adjusted series in Appendix Figure A2). The different patterns over time show that a decline in the middle class cannot be examined in isolation from the larger context, and may be a positive or negative development for workers depending on how other employment shares evolve. In none of these three phases is polarization evident for men, which in the 2003–2012 period is due to the lack of rise in the share in the top bin.

4.3 Oaxaca decompositions into characteristics and returns

It is interesting in its own right to analyze which factors are associated with changes in the shares of workers in wage bins, and of particular interest here to study the role of occupations and assess whether any factor is tending to polarize employment. To do so, we perform Oaxaca decompositions of changes in employment shares into changes in characteristics and their returns, presenting the results for certain longer periods and their standard errors in panel A of Appendix Tables 3 and 4. We focus our discussion on graphical results of the year–to–year decompositions (without standard errors). In Figures 10 for women and 11 for men, we first plot the predicted shares of workers in each wage bin for reference (in solid blue): note that the y-axis scales differ across graphs. With green triangles, we plot the contributions of changes in characteristics by adding the yearly contributions cumulatively to the 1983 share: this is how the shares would have evolved if only the worker characteristics had changed. With red squares, we plot how the shares would have changed had only the returns to characteristics changed.

The figures show that improving characteristics have caused upward mobility, especially for women, and no polarization. Improving characteristics have moved women steadily up the wage groups, reducing the share in the lower two wage groups (especially the bottom, which fell seven percentage points) and increasing the share in the upper two (since 1993 the top only, with an increase of about nine percentage points). Improving characteristics reduced the share of men in all three lower wage groups fairly steadily, increasing the share in the top group by about five percentage points. Appendix Figures A3 and A4, which replicate the figures for decompositions without occupation as a characteristic, show that the contribution of changes in characteristics is not very sensitive to the inclusion of occupation, as its contribution comes to some extent at the expense of increasing education.

Fluctuations in the predicted employment shares are reflected in fluctuating returns to characteristics for both men and women. For women (Figure 10), the trends in the return to characteristics are similar to the trends in the characteristics, leading to upward mobility through the wage bins. The same is not true for men (Figure 11). Changes in returns to characteristics moved male workers from the upper middle bin to the lower middle, while having little long–run effect on the share in the top and bottom bins over the 1983–2018 period. For men, the surge in the share in the top bin and the post-1983 decline in the share in the bottom bin are thus driven entirely by improving characteristics.

4.4 Role of changes in specific characteristics

We next present yearly graphs with the more detailed contributions of specific characteristics for 1983–2018 (results for longer periods are presented with standard errors in panel B of Appendix Tables 3 and 4). We do not find any characteristic to have a polarizing effect (tending to increase the share of workers in the top and bottom bins), and we do not find that shifts in the occupational composition of employment have increased the share of workers in the bottom bin.

Figures 12 and 13 report, for men and women separately, the contributions of specific characteristics to the changes in employment shares (the results without occupation are presented in Appendix Figures A3 and A4). These contributions are generally steady and monotonic. For both men and women, the most influential characteristic is education, whose increase caused upward mobility from the lower two to the upper two wage groups (for women) and to the top wage group (for men). Increased education reduced the share of women in the bottom group by about four percentage points and increased the share in the top by about five percentage points, while it reduced the share of men in the bottom by about two percentage points and increased the share in the top by more than three percentage points.

For women, occupation is the second most influential characteristic, followed by age, with other characteristics playing only minor roles. For men, age is almost as influential as education, with occupation somewhat less influential than for women, but other characteristics are also important. Rising age and improving occupation quality are associated with upward wage mobility for both genders, though the role of age ends around 2005. For men, deunionization is a powerful force for downward mobility if not as large in absolute value as age and occupation effects, while changes in industrial composition are also associated with downward wage mobility. Closer inspection of the occupation effects shows that changes in occupation are initially associated with women moving from the lower two bins to the upper two bins, but from roughly 2001 cease to be associated with changes in the bottom bin and instead are associated with movement from the middle bins to the top bin. For men, changing occupation has negligible effects on the share in the bottom bin, and is always associated with mobility from the middle bins to the top bins. Appendix Figures A7 and A8 show that occupation effects on the bottom bin are qualitatively the same with ten wage bins.[22]

5 Is employment polarizing based on the Foster–Wolfson measure?

A different way of checking whether rising wages are obscuring polarization is to use a measure of polarization that is invariant to the median wage. In Figure 14, we compare the 1973 and 2018 wage distributions using the method proposed by Foster and Wolfson (2009). By definition, a Foster–Wolfson curve equals zero at the 50th percentile since the distance of the median wage from the median wage is always zero, while the (mean) distance of other wage percentiles from the median is positive. Polarization would require that the two arms of the 2018 distribution be above the two arms of the 1973 distribution except at the median. The figure shows that wages above the median have indeed moved farther away from the median (the right arm pivots up from the median), and an

[22] The presence of only small jumps in the plots for industry and occupation suggest the code harmonizations are satisfactory in this context.

unreported, more detailed figure shows that there is no temporary reversal of this trend. However, changes below the median are close to invisible at the scale of Figure 14. An unreported figure at a finer scale shows a pivot upwards below the median between 1973 and 2018, with a partial reversal between 2012 and 2018, and changes between 1973 and 2012 that sometimes involve crossing curves. Though this strictly speaking implies an upward pivot of both arms and hence polarization between 1973 and 2018, it is clear that all meaningful movement involves the upper half of the distribution pulling away from the median.

6 Occupation–based analysis

We turn now to the study of employment polarization and wage inequality through the lens of occupations, first considering how informative occupation average wages can be for individual–based wage inequality, then noting other problems with occupation–based analysis, and finally synthesizing results from the individual and occupation–based analysis.

6.1 Suitability of occupations for studying wages

The ultimate objective of many papers on employment polarization is to explain the causes of rising wage inequality, often represented by economists as the difference in log wages at the 90th, 50th and 10th percentiles. However, Figure 15 shows that mean occupation wages cannot capture movements in the bottom of the wage distribution: only three of the 330 standardized occupations (including the agricultural occupations dropped by the U.S. literature) have mean 1983 wages at or below the 10th percentile of the individual wage distribution in 1983, and only five have mean wages below the 20th percentile of the individual wage distribution. Figure 16 shows that the problem confronting the polarization literature is worse, since the literature groups workers into percentiles based on their occupation and its mean wage: the bottom percentile is at approximately the 10th percentile of the 1983 individual wage distribution while the second-to-bottom percentile is at approximately the 20th percentile. Clearly, changes in employment or wages by these occupation–based percentiles will at best reflect changes in employment of low-wage workers only crudely.

The problem is not merely that the bottom 20 percent of workers are represented by only two of 100 categories, however. Many workers in the bottom occupation–based percentiles are not low-paid workers, as we saw in Figure 7. For example, only half of workers in the bottom occupation–based percentile have wages in the bottom 10 percent of the overall wage distribution. The lack of mapping between the two types of percentile is even more clear when considering the middle of the distribution. Figure 17 shows the share of workers in each occupation–based percentile who earn between the 40th percentile and median of the overall wage distribution: the shares are remarkably uniform and therefore low even in the middle (no percentile has a share of such workers over 17 percent). One therefore cannot think of the middle occupation–based percentiles as mapping to middle-wage workers. Goos and Manning (2007) address this problem in their simulation of the effect of British occupation–based employment polarization on wage inequality by allowing for a distribution of wages within occupation which they hold fixed as occupation employment shares evolve. We are not aware of a similar simulation for the United States, and we do not view occupation mean wages alone as an appropriate lens through which to study wage inequality.

6.2 Is employment really polarizing based on occupations?

Despite the unsuitability of occupations as a means of studying wage inequality, it is worth pointing out that even on its own terms, occupation–based analysis does not show employment polarization except in the 2002–2012 period. In this section, we use the CPS to investigate the prior census–based results best summarized by Figure 18, from Autor (2015a). Employment shares rise for both the top and bottom occupations in the 1989–1999 period and in the 2007–2012 period (the post–1999 data come from the American Community Survey), and the share in the bottom occupations also rises in the 1999–2007 period. There does not appear to be polarization in the 1979–1989 period: although employment share falls more around the 20th percentile of the occupation distribution than at the bottom, the fall for all except the very lowest percentile is instead indicative of occupational upgrading (workers moving up the occupational ladder), as noted by Mishel, Shierholz and Schmidt (2013). By contrast, Autor (2015a) interprets this pattern as polarization.[23]

If occupation–based polarization began around 1989, the timing could be consistent with a slightly delayed influence of computerization and automation, factors which may

[23] In Autor (2010), the employment share at the bottom falls as much as in the middle in 1989–1999.

also have been behind the 1990s productivity boom. There is no disagreement that the employment share of high–wage occupations has been rising steadily over time, so a simple way of testing for polarization is simply to plot an annual time series of the employment share of bottom occupations to see if and when it rises. In Figure 19, we plot the raw employment shares of the low–wage occupations cumulatively employing 10% of workers, without ("baseline") and with health and nursing aides, as well the employment share of the subset of occupations considered service occupations by Autor and Dorn (2013), without health and nursing aides. We choose the bottom 10% because when the share of low–wage occupations rises in the existing literature, the rise is seen for the bottom 10% (see Figure 18). These series are not adjusted for occupation code breaks in 1983 and 2000, nor for the 1994 CPS redesign. The main effect of the 2000 code break is obvious in the figure: it causes low–wage occupations to expand. This could lie behind the apparent rise in low–wage employment for 1989–1999 in Autor (2015a), since in the Census data, observations for 1999 use the new 2000 codes.

To see this more clearly, we adjust the series for the breaks. For the 1982–1983 and 1993–1994 breaks, we assume the growth in employment share is the average of the preceding and succeeding pairs of years. We normalize the 2000–2002 overlapping shares to be equal in 2002. Close scrutiny of the overlapping years 2000–2002 in Figure 19 shows that the change in occupation codes also led to higher employment growth (in addition to a higher level), but we do not attempt to adjust for this. All three adjusted series, plotted in Figure 20, indicate that there was no trend in low–wage occupation employment share until about 2002, then growth until about 2012. We also plot the employment share using the slightly different set of bottom 10 percentile occupations from Autor and Dorn (2013), without health and nursing aides which in their data as in ours straddle the 10th percentile. The difference between this series and the baseline is small. When we allow the bottom 10% of workers to be based on occupations including those in agriculture, (excluding health and nursing aides), there is a clear downward trend in low–wage occupation share through 1999. The subset of occupations defined as service occupations by Autor and Dorn (2013) have a rise in employment share in the early 1980s, then no change until growth resumes in about 2001. This figure shows that employment polarization—which requires growth in the bottom employment share—could not have occurred before 2001.[24]

[24] The service occupation series may appear to contradict Figure 3 in Autor and Dorn (2013), which shows an increase in low–wage service–occupation employment share for 1979–1989, a period without a serious occupation code break. When the definition of low–wage occupation workers is expanded to

To assess the full employment polarization picture and make the same point in a different way, we focus in Figure 21 on the 1989–1999 period which so clearly shows polarization in Autor (2015a). We first plot the raw 1989–1999 curve from the CPS (purple triangles); this shows employment decline at the bottom. However, when we adjust for the 1994 redesign, simply by assuming there are no genuine changes in 1993–1994 (Appendix Figure A9 suggests this is likely to be approximately true, since there is almost no change in 1992–1993 and 1994–1995) and subtracting the apparent changes, growth at the bottom is slightly positive (solid gold line). This curve represents our preferred implementation of the occupation–based approach using CPS data.

However, this curve is qualitatively different from that of Autor (2015a), and further adjustments are necessary to reconcile the two. Accordingly, we extend the period covered by the analysis to 2000 without crossing a code break, which makes almost no difference to the curve (blue x's). Finally, we also plot the curve for the same period but intentionally using the new occupation codes in 2000 used in the census–based analysis: now there is considerable growth in employment shares of bottom occupations (as well as top occupations), similar to the 1989–1999 curve in Autor (2015) (red plus signs). Although we use our own occupation ordering in the figure, the results change very little if we use the Autor and Dorn (2013) occupation ordering (results not reported). Polarization in 1989–1999, which would require an increase in the employment share of the bottom group, is an artefact of the code break.

To complete the analysis, we show in Figure 22 the curves for 2000–2010 and 2011–2018.[25] There is clear polarization in the earlier period, and no polarization in the later period, consistent with our series on the share of employment due to low–wage occupations. Figure 23 shows the evolution for the entire 1983–2018 period, contrasting the fully adjusted curve with the curve not adjusted for the occupation code break.

The final series of interest, plotted in Figure 24, are for low–wage occupation women and men separately as a share of employment, and the corresponding shares for college and non–college workers. The shares of women and non–college are falling over time. For women, the decline ends around 2000, and in a mechanical sense it is this that leads to the

be comparable with Autor and Dorn (occupations representing 20% of workers rather than 10% as in Figure 19), this share does have a slight upward trend from 1973–1991. However, the trend is larger by a factor of two in Autor and Dorn due to the unusually low share in 1979 (figure available from the authors upon request).

[25] We avoid plotting 2010–2011 because of the transition from Dorn to Hershbein and Jacome occupation codes, which implies a change in the number of occupations.

increase in the low–wage occupation share after that point, since the share of men grows steadily until 2012, when it plateaus and then declines. Low–wage occupation non–college workers (some college or less) decline slightly over time as a share of employment, while their college counterparts' share rises from close to zero in 1973 to about one percent in 2018. On the other hand, as pointed out by Autor (2019), non–college workers are polarizing when studied in isolation (results not shown), which may indicate that underlying occupation–based employment polarization is masked by human capital–driven occupational upgrading of workers. This cannot plausibly be investigated by predicting the evolution of the occupation distribution with age and education fixed, however: it is unlikely that the employment decline in low–wage occupations caused by rising human capital occurs at the rate implied by the cross–sectional correlation between human capital and occupation.

6.3 Synthesis of wage bin and occupation analysis of low–wage jobs

We can synthesize by period the major patterns outlined by our wage bin and occupation analyses. Prior to 2002, the share of employment that is in low–paid occupations is stable, the result of exiting women being replaced by entering men. Women's exits tend to reduce the share of workers in the bottom wage bin (as shown by the effect of occupations in the Oaxaca decomposition), while men's entry has little effect on the share of men in the bottom wage bin because few of these entrants earned bottom bin wages (at most 22% of men in low–wage occupations were in the bottom of four wage bins, and at most 10% in the bottom of ten wage bins over 1973–2018). The share of workers in the bottom wage bin is further reduced by wage increases for women in the lowest–paid occupations, due in part to rising age and education, and in part to changes in returns to characteristics. Men's wages in the lowest occupations do not increase, because rising age and education are offset by declining unionization and changing industry, and wages are not boosted by changing returns to characteristics, whose effects seem to be principally cyclical throughout the study period.

Employment in low–paid occupations grows from about 2002 to 2012, due to a stalling of women's progression into higher occupations and continued entry of men. The share of workers in the bottom wage bin also grows at this time. The stalling of women's occupational upgrading means that changing occupations are no longer associated with a falling share of women in the bottom wage bin, while at around the same time, age ceases to reduce the share of women (and men) in the bottom wage bin. The boost provided by changes in characteristics thus weakens just as changes in returns begin to increase rather than decrease the share of women in the bottom wage bin, and also as occupation codes change in a way that may have increased apparent low–wage occupation growth. The net result is that the trend downwards in the share of women in the bottom ends and is replaced by cycles (a related trend may be the plateauing of women's labor force participation, not studied here). For men, the favorable effects of returns to characteristics in the 1990s boom switch to become unfavorable, with changes in characteristics continuing to have little effect, leaving patterns in the share in the bottom wage bin qualitatively similar to those for women.

Finally, from 2012, the share of workers in low–paid occupations plateaus and then falls, reversing most of the 2002–2012 increase. The reversal is less marked if the booming health and nursing aides are included: the exceptional growth in health and nursing aides reflects not only an aging population, but also the introduction in 2000 of more favorable Medicare payments for home health care (Wu 2019). The shrinking employment share of low–wage occupations combined with the rising wages within these occupations (see Figure 7) are consistent with this period also corresponding to a large fall in the share of workers in the bottom wage bin. The Oaxaca decompositions indicate that the most powerful force from 2012 is changing in returns to characteristics, affecting both men and women, and surely including a strong business cycle component.

7 Conclusion

We re–examine whether U.S. workers are increasingly concentrated in both low and high–wage jobs, a phenomenon known as employment polarization. We depart from most previous literature, which equates a job with an occupation, by instead considering jobs at the individual level. By assigning workers in the CPS to real hourly wage bins with time-invariant thresholds and tracking over time the shares of workers in each, we find a steady decline since 1973 in the share of workers earning middle wages, consistent with occupation–based analysis. However, we find that both over the business cycle and the longer run, the shares of workers in the top and bottom bins move in opposite directions, inconsistent with employment polarization.

The slight downward trend in the share of workers with low wages could in principle coexist with the growing employment share of low–wage occupations found in the literature: we show that the share of low–wage occupation workers with low wages falls greatly with time. However, we also show that the share of employment in low–wage occupations is trending up only from 2002–2012, and that the apparent earlier growth found in the literature is an artefact of unbridgeable changes in occupation codes. The late emergence of occupation–based polarization is inconsistent with the explanation that computerization and automation have caused both employment polarization and rising wage inequality, unless underlying occupation–based employment polarization in earlier periods was masked by human capital–driven occupational upgrading of workers.

We demonstrate that even absent breaks in occupation codes, occupation mean wages are unsuitable for the analysis of wage inequality: most of the increase in wage inequality is within and not between occupation; occupation mean wages do not capture the bottom of the individual wage distribution; and middle–wage workers are distributed widely across occupations. Computerization and automation may be increasing wage inequality, but the hypothesis cannot be studied through the lens of occupations and does not find support in our analysis.

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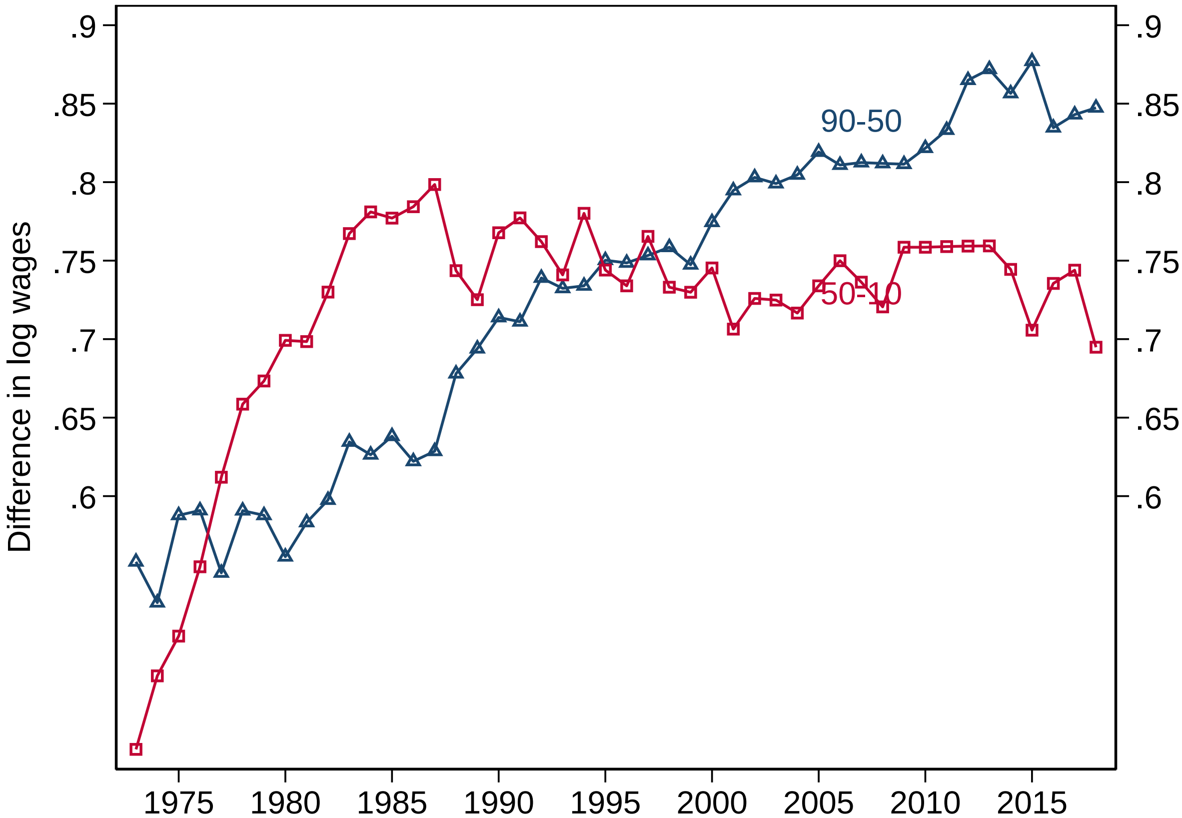
Data Appendix: Harmonization of industry codes

The basis for the harmonization of the industry codes is the aggregate industry codes in the NBER MORG extracts. The NBER itself combines the 1970, 1980 and 1990 codes to generate 48 harmonized aggregate codes, leaving the main task the harmonization of this set of codes with the 2000 aggregate codes. Our general approach is to make the later codes conform to the earlier codes, but we do make some changes to the earlier codes. We reassign those in the 1970–1990 agricultural services category (which does not exist in the 2000 codes) based on their detailed industry code to other professional services (veterinary services), business services (landscaping and horticultural services) or agriculture (other agricultural services). We also split the 1970–1990 retail trade and food services category into two (retail trade, food services). The largest set of changes to the 2000 codes involve the professional and technical services and administrative and support services categories, which crudely correspond to other professional services and business services respectively. However, we reassign specialized design services, computer systems design and related, management, scientific and technical consulting, and advertising and related services from professional and technical services to business services; the aggregate category of membership associations and organizations to other professional services; rental and leasing services from rental/leasing to business services (except video leasing, which is assigned to arts and entertainment); data processing from other information services to business services; travel services from administrative and support services to transportation. We also change the 2000 codes so as to move librarians from other information services to educational services. We merge the 2000 categories (and in some cases 1970–1990 categores) of agriculture and forestry; beverage and tobacco production; petroleum/coal and mining; primary, fabricated and not specified metals; furniture and wood; paper and printing, textiles, apparel and leather; aircrafts and parts, motor vehicles and parts, and transportation equipment; toys/amusements/sporting goods, professional and photographic equipment, miscellaneous manufacturing; accomodation and personal and laundry services; broadcasting, telecommunications, internet publishing and broadcasting and internet services and data provision; paper/printing and publishing; electrical machinery production and computer and electronics production. Some of these merges are done because the more detailed categories are small.

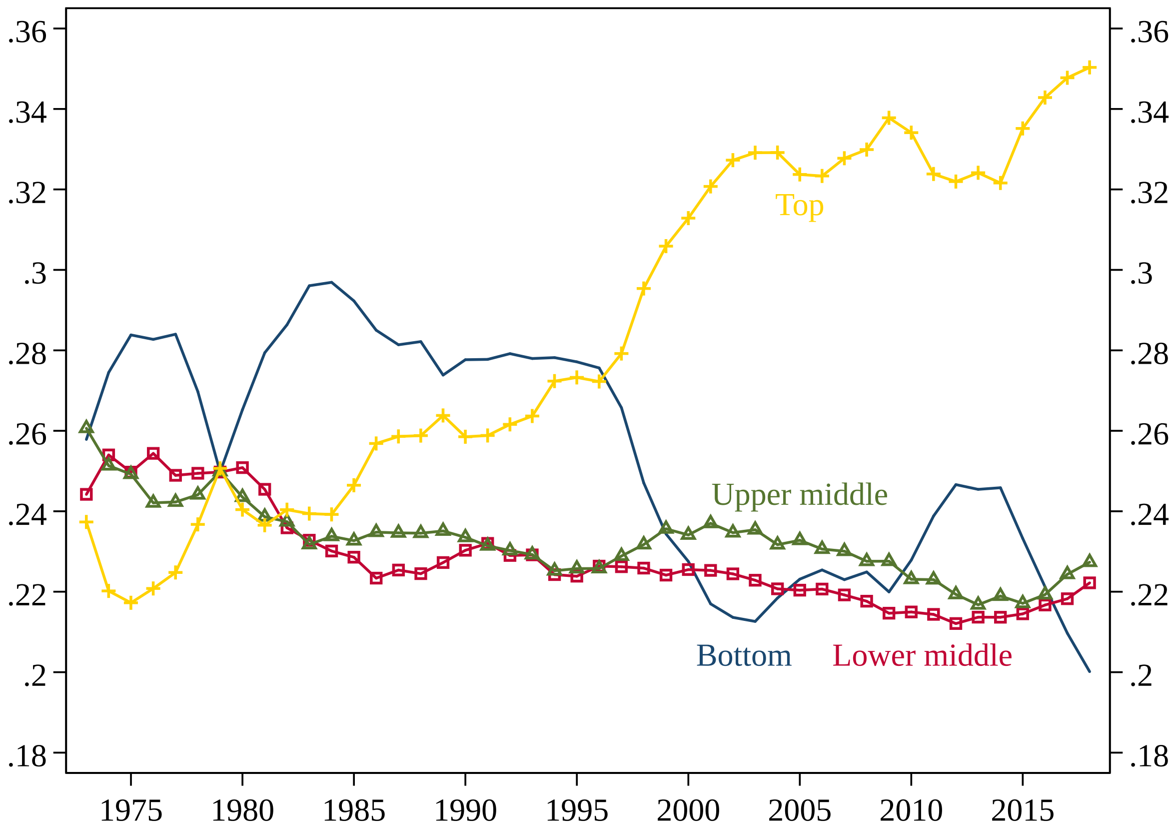
Figure 1: Summary inequality measures, 1973–2018



Note: Difference between 90th and median log hourly wages (90–50) and median and 10th percentile wages (50–10), weighted by weekly hours work. Non–self employed workers 18–64 without missing values for covariates used elsewhere in the paper, but including imputed values.

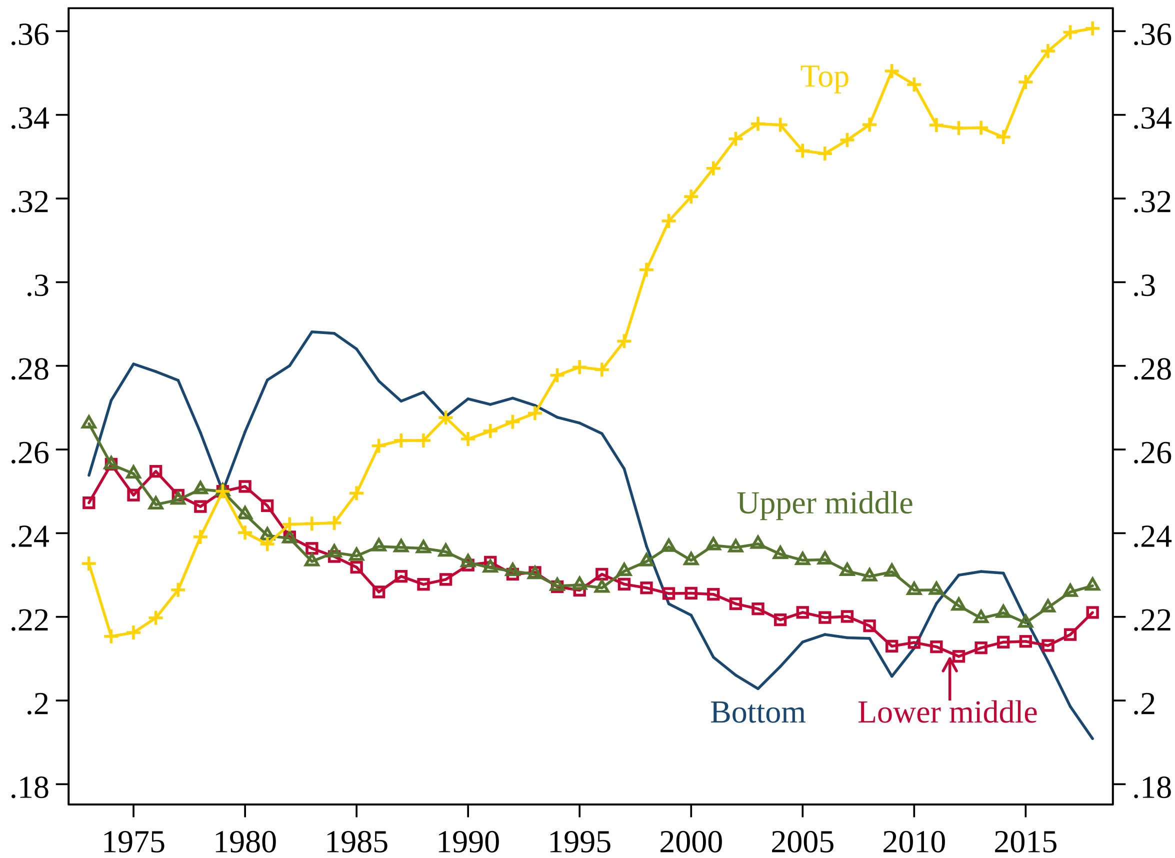
Source: CPS MORGs 1979–2018 and CPS Mays 1973–1979.

Figure 2: Shares of workers in four wage bins, 1973–2018



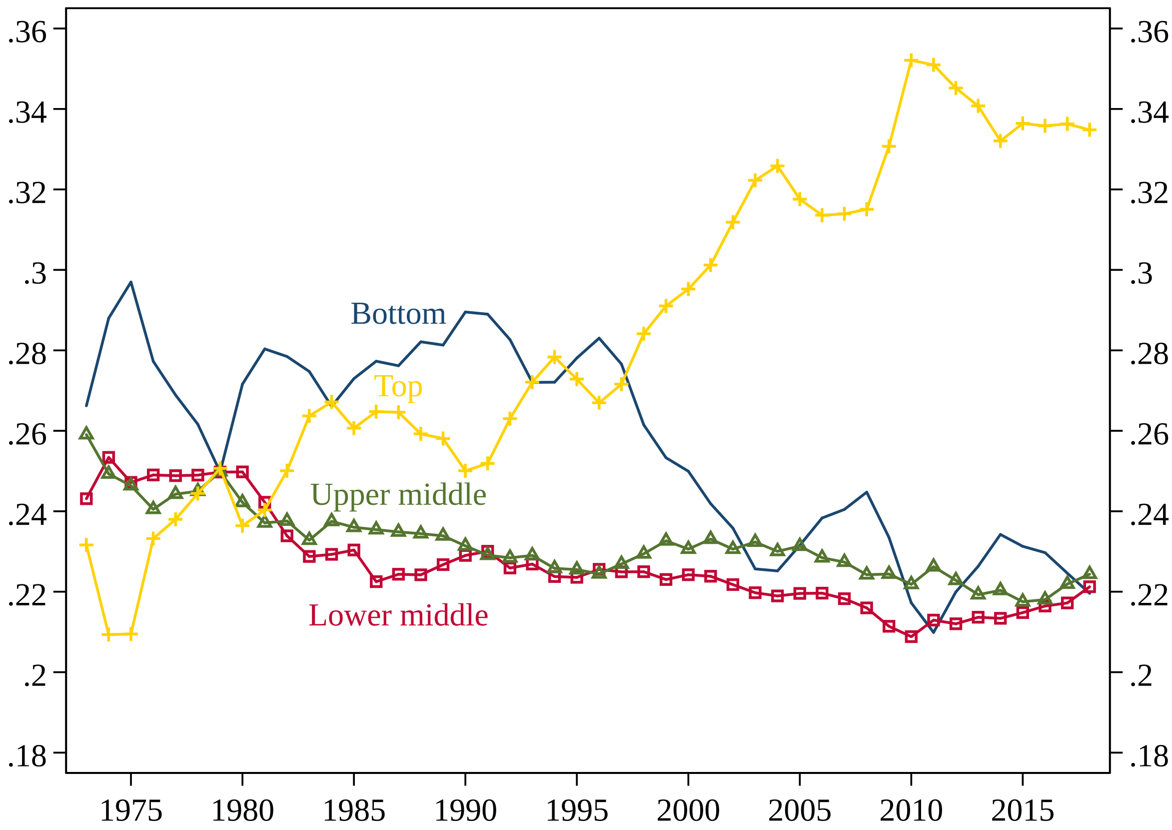
Note: Real wage bin thresholds are defined based on 1979 quartiles.

Figure 3: Shares of workers in four wage bins, weighted by worker hours, 1973–2018



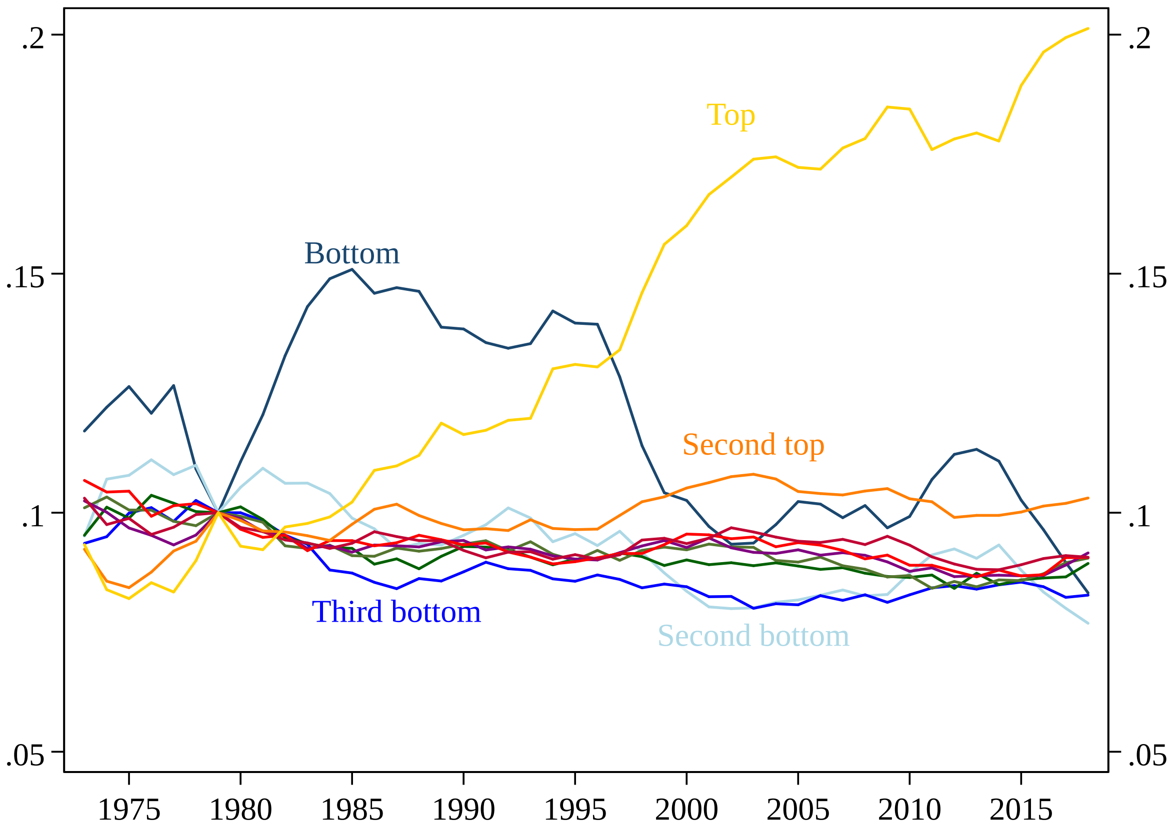
Note: Real wage bin thresholds are defined based on 1979 quartiles.

Figure 4: Shares of workers adjusted for the business cycle, 1973–2018



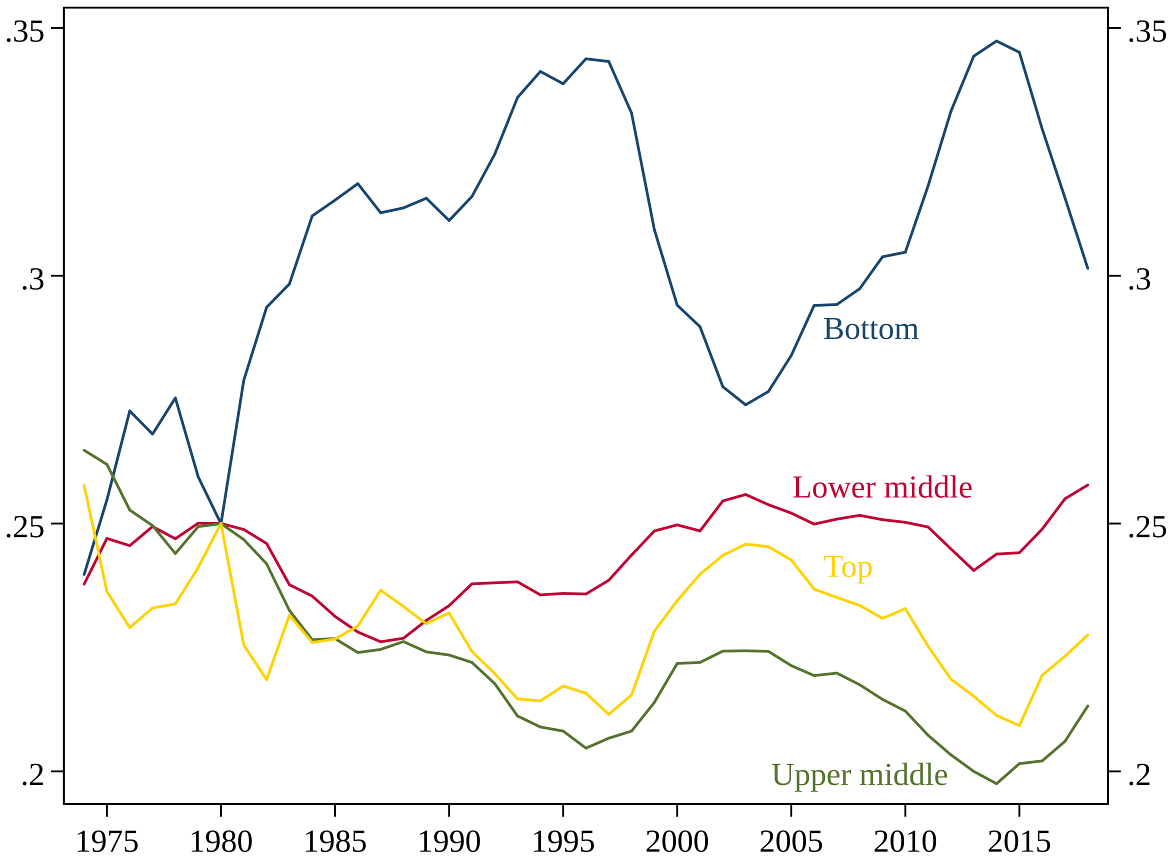
Note: Real wage bin thresholds are defined based on 1979 quartiles.

Figure 5: Shares of workers in ten wage bins, 1973–2018



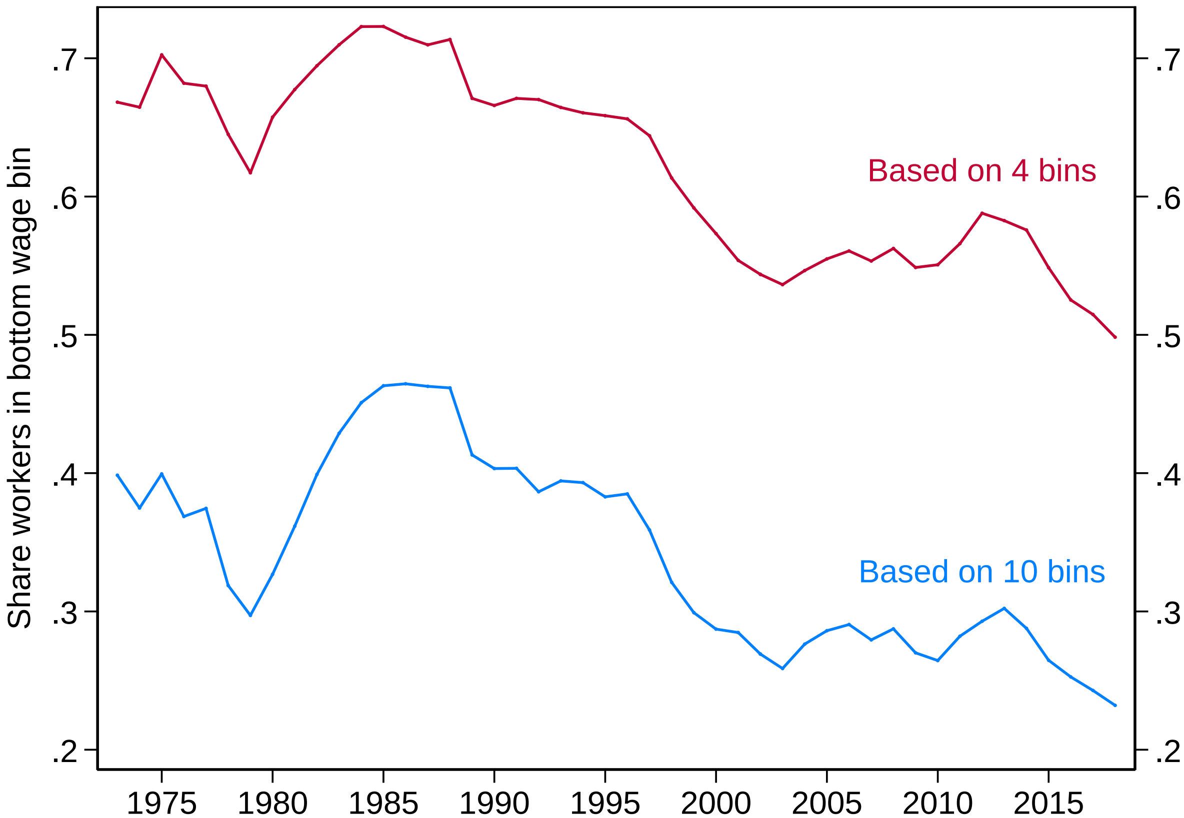
Note: Real wage bin thresholds are defined based on 1979 deciles.

Figure 6: Shares of workers in wage bins; age and education fixed at 1979



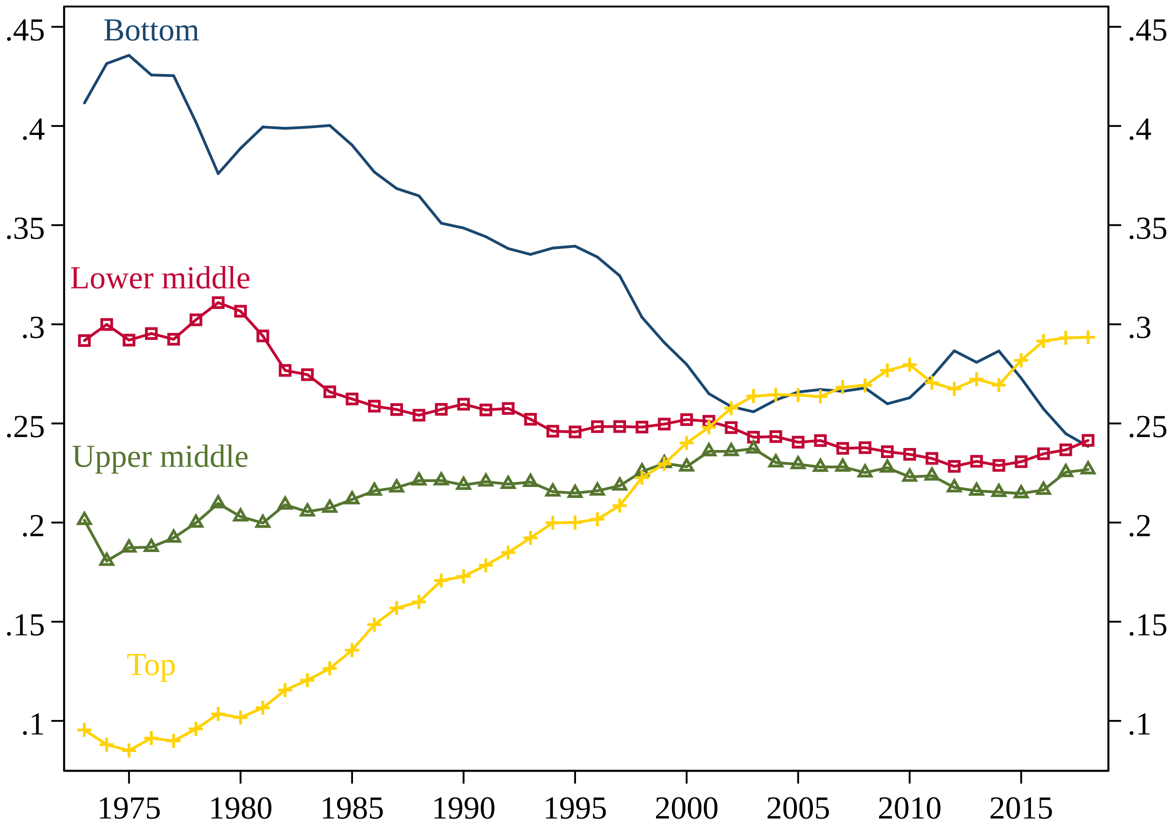
Note: Real wage bin thresholds are defined based on 1979 quartiles.

Figure 7: Share of workers in low–wage occupations who are in bottom wage bin



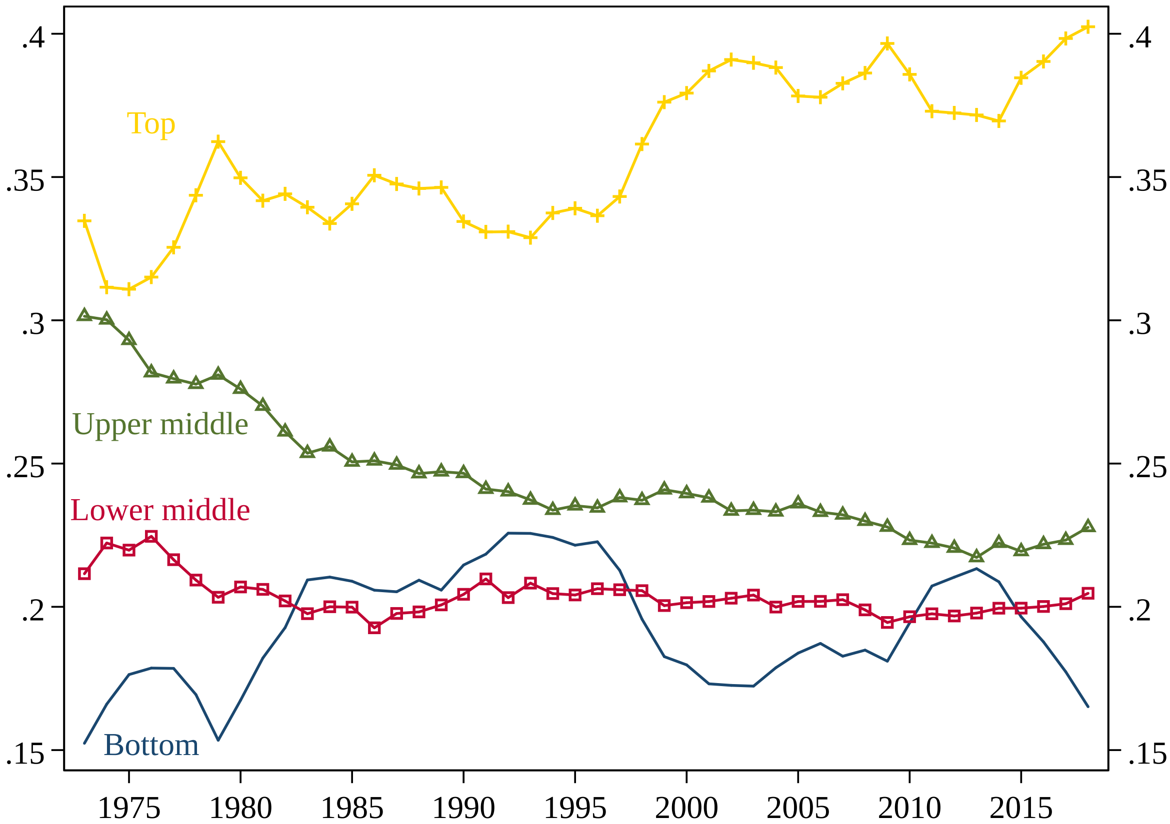
Notes: Occupations are ranked based on 1983 average wages and the bottom–paid occupations are those occupying 10% of workers, excluding health and nursing aides. The bottom wage bin is based either on quartiles or deciles in 1979. To harmonize breaks due to the 1994 CPS redesign and the new occupation codes in 1983, the 1993–1994 and 1982–1983 growths are the average of prior and subsequent pairs of years; to harmonize across the 2000 occupation code break, the 2002 level with the new codes is normalized to equal the 2002 level with the old codes.

Figure 8: Shares of women in four wage bins, 1973–2018



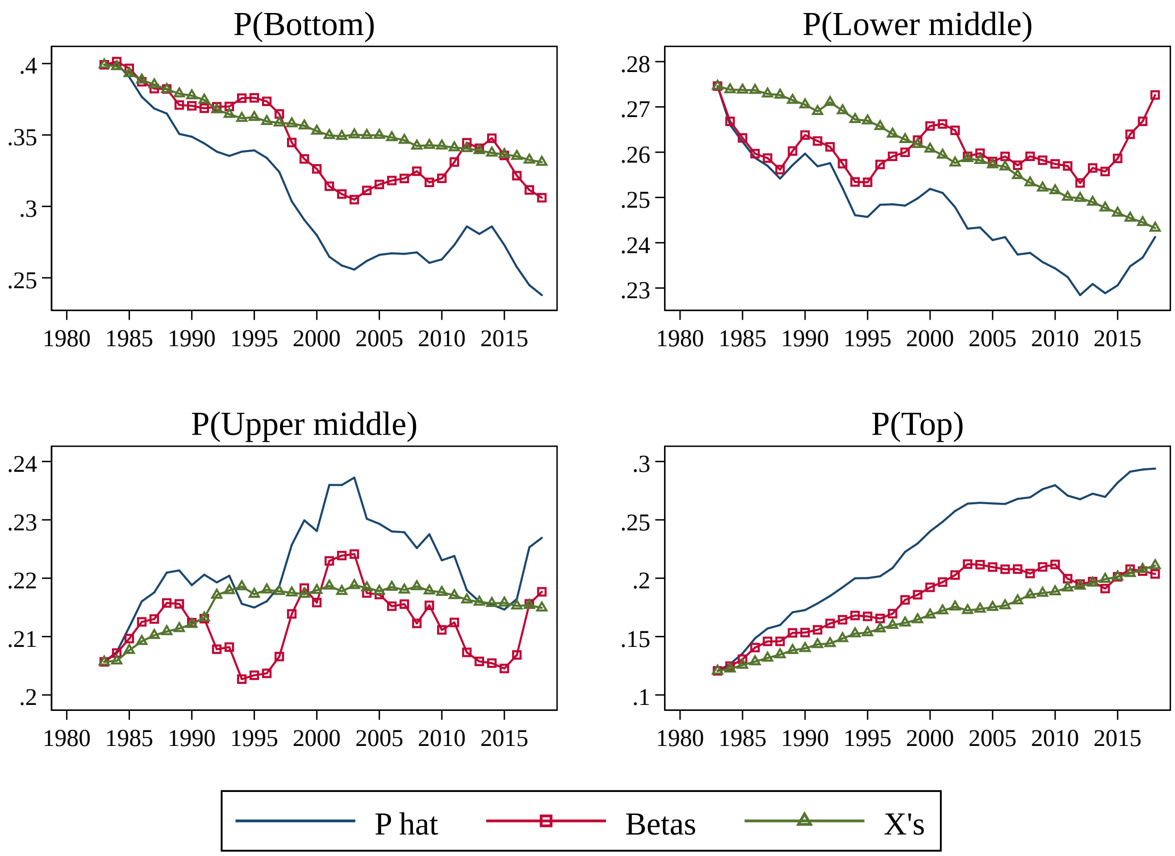
Note: Real wage bin thresholds are defined based on 1979 quartiles for pooled women and men.

Figure 9: Shares of men in four wage bins, 1973–2018



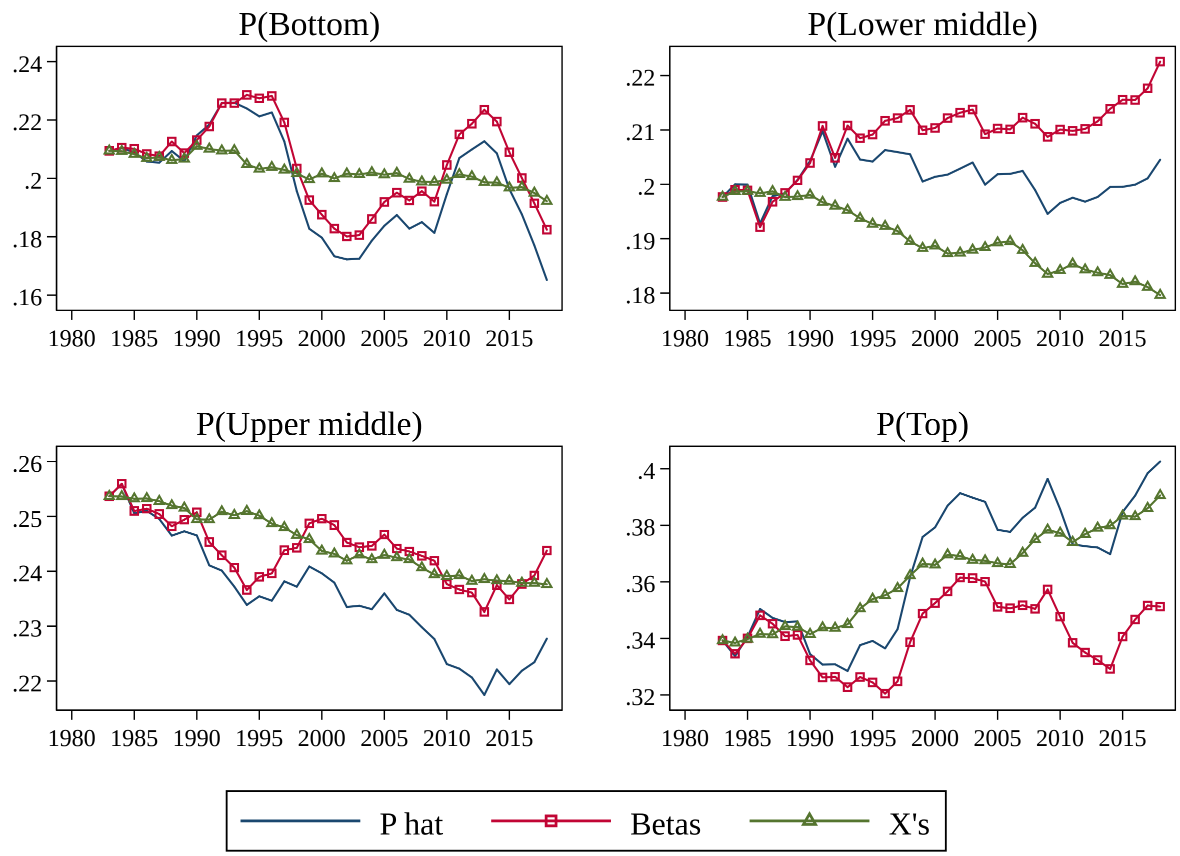
Note: Real wage bin thresholds are defined based on 1979 quartiles for pooled women and men.

Figure 10: Predicted shares and their components 1983–2018 – women



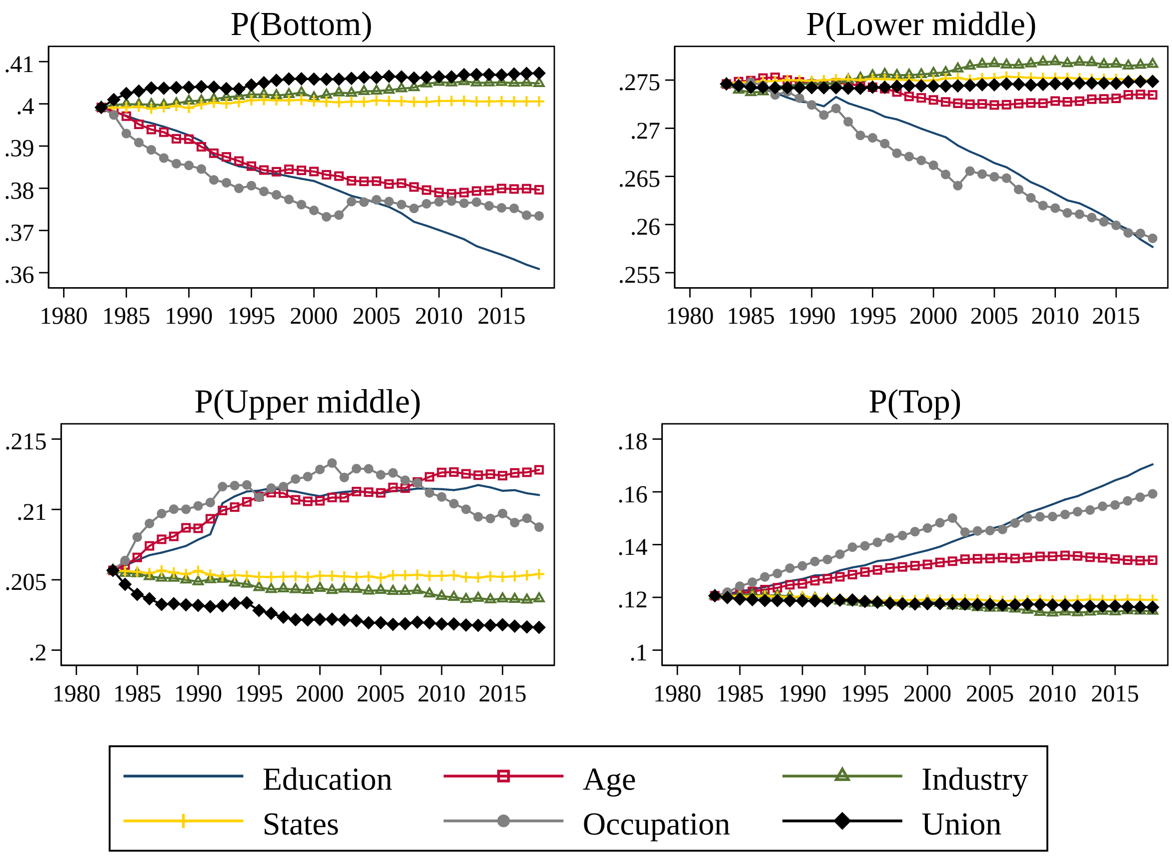
Note: Oaxaca decomposition based on education, age, state, union status, industry and occupation.

Figure 11: Predicted shares and their components 1983–2018 – men



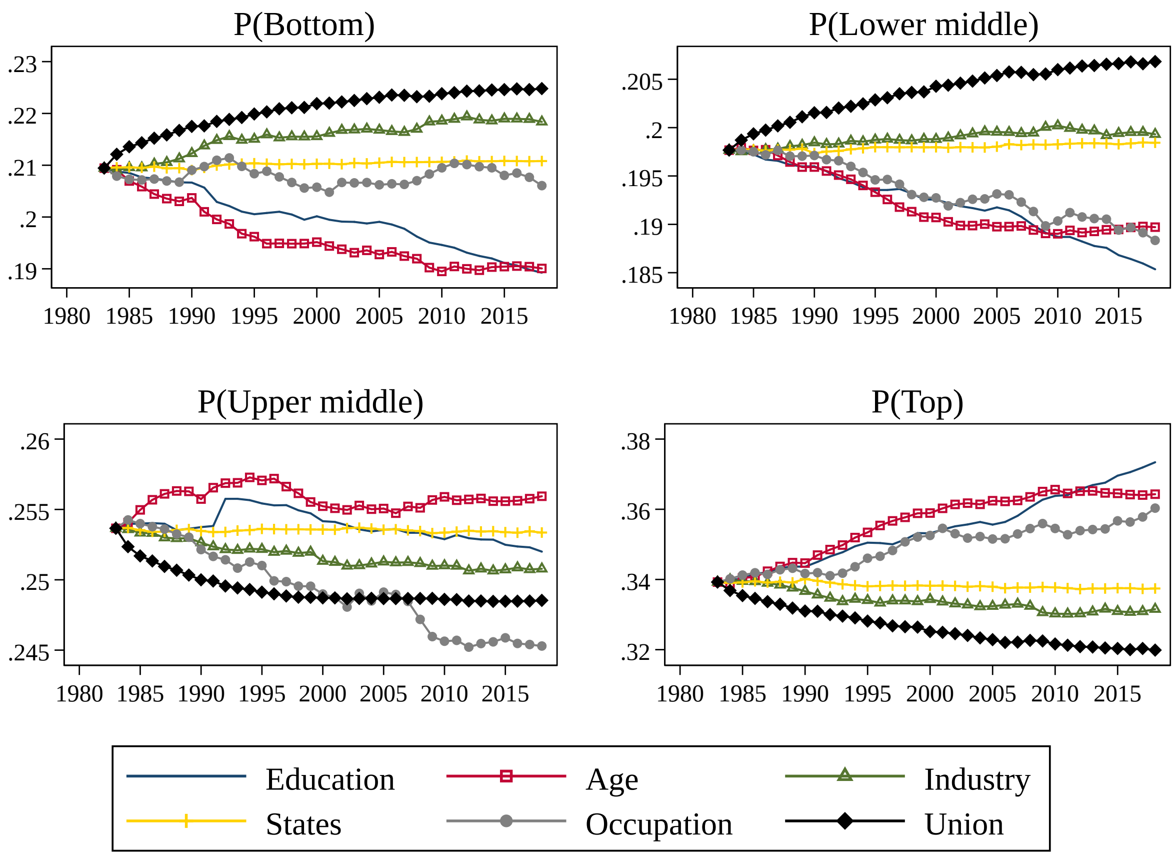
Note: Oaxaca decomposition based on education, age, state, union status, industry and occupation.

Figure 12: Contributions of individual X's 1983–2018 – women



Note: Oaxaca decomposition based on education, age, state, union status, industry and occupation.

Figure 13: Contributions of individual X's 1983–2018 – men



Note: Oaxaca decomposition based on education, age, state, union status, industry and occupation.

Figure 14: Foster and Wolfson (2009) test for polarization

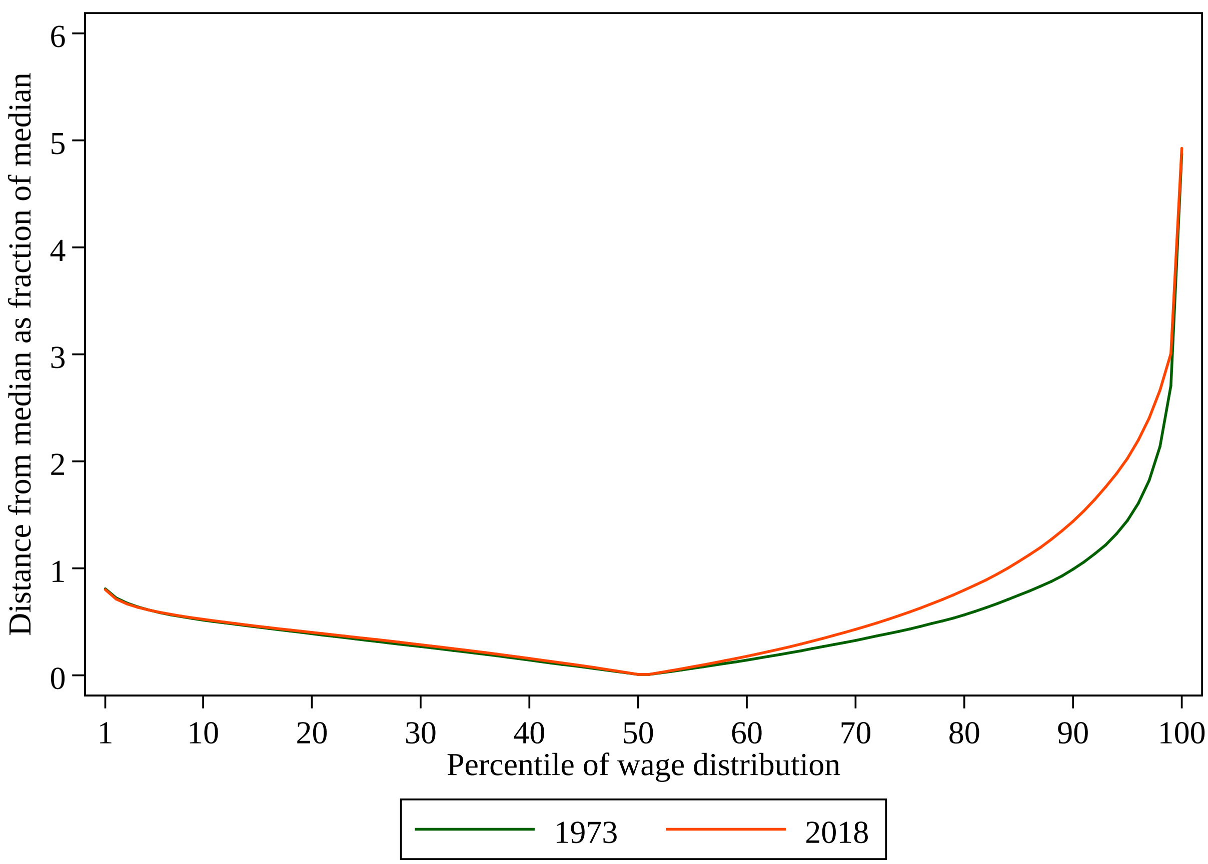
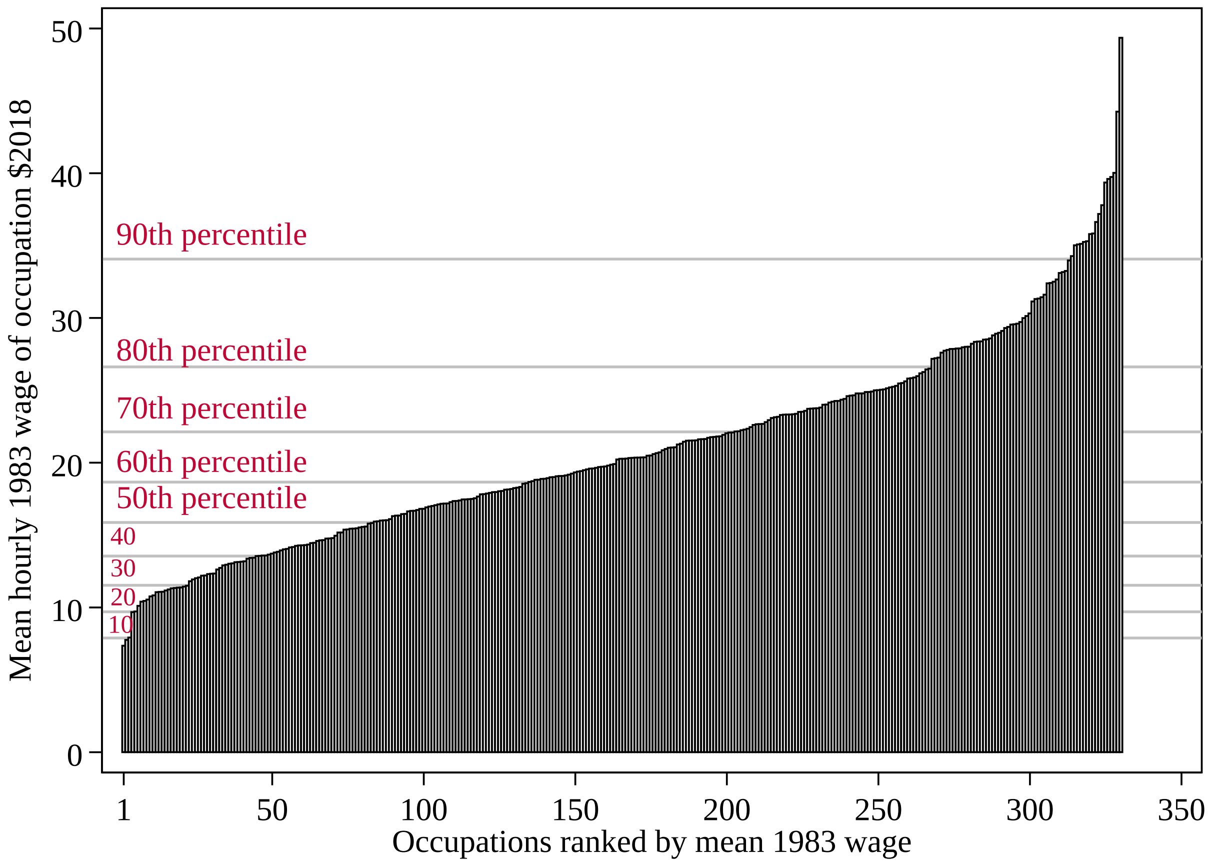
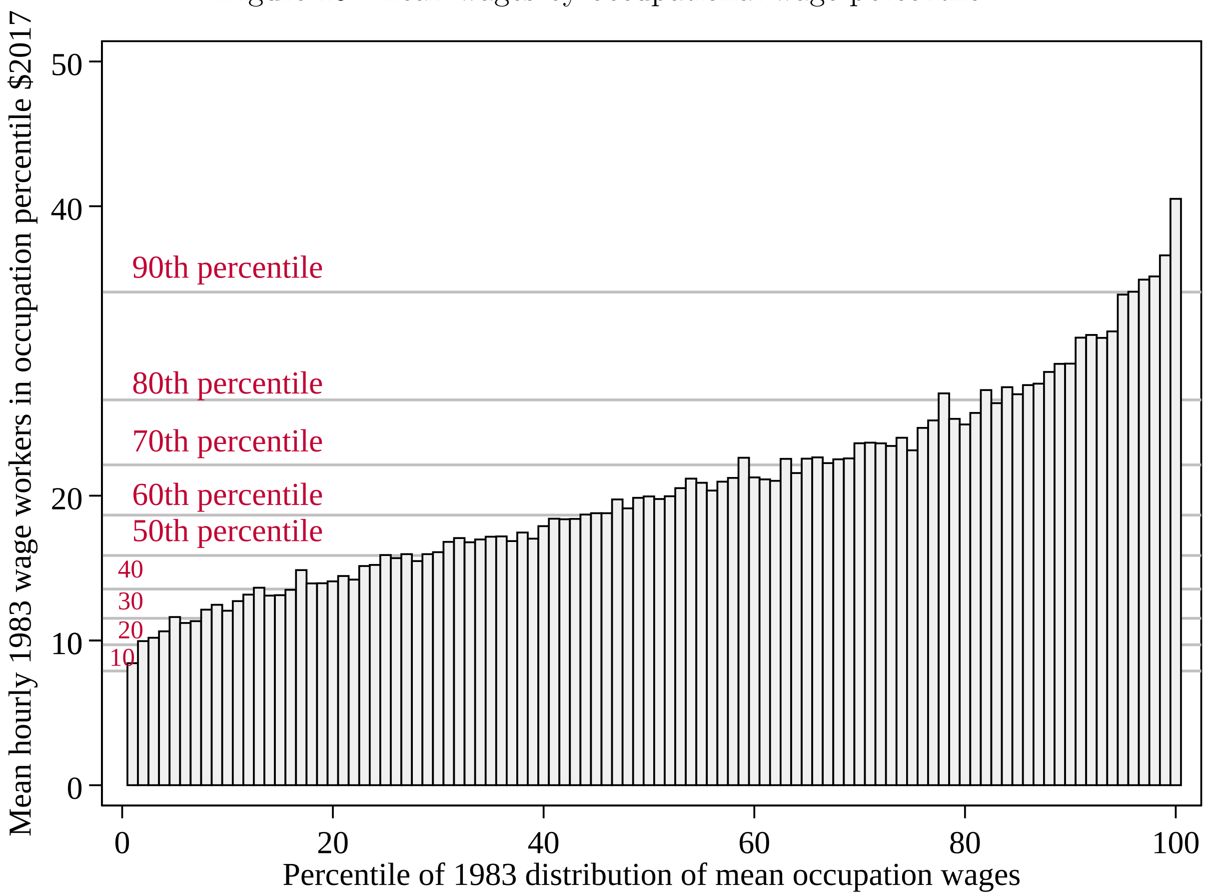


Figure 15: Mean wages by occupation



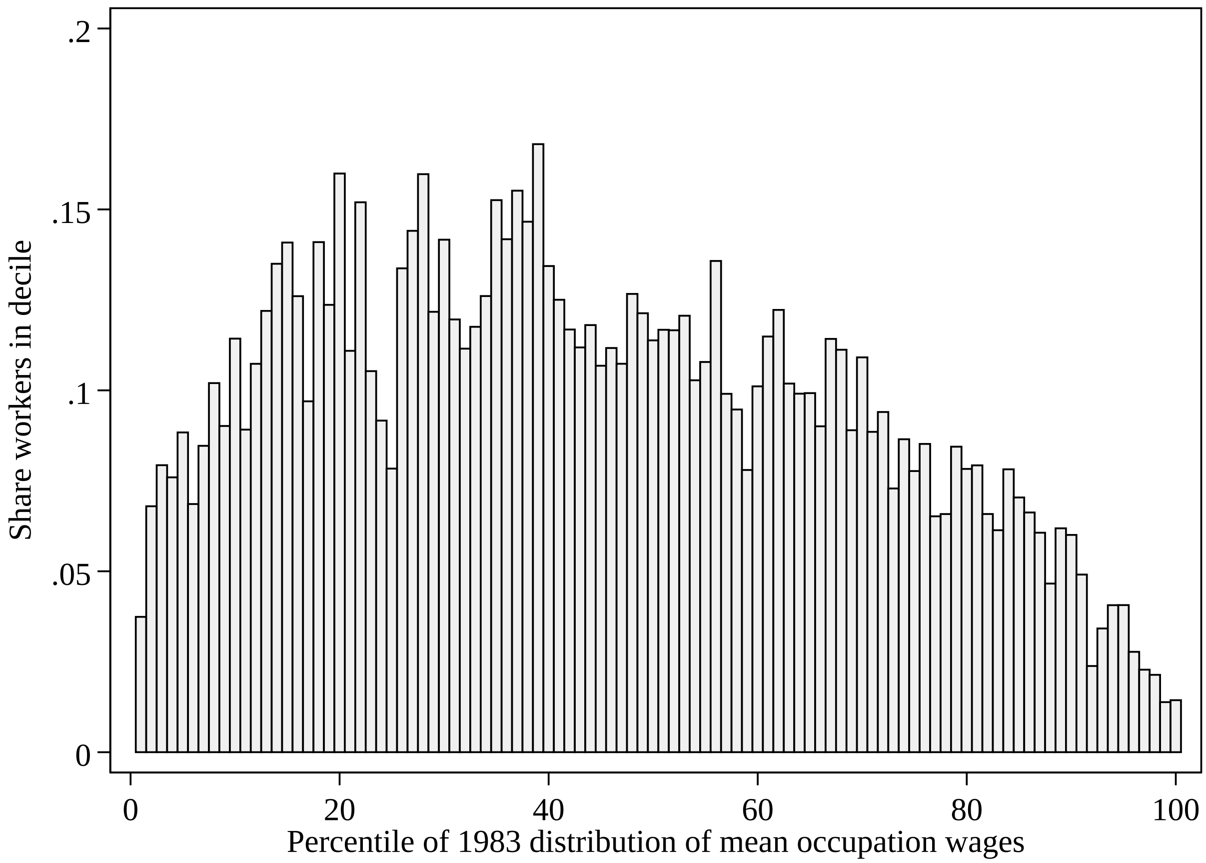
Note: Horizontal lines refer to percentiles of the wage distribution. 330 occupations.

Figure 16: Mean wages by occupational wage percentile



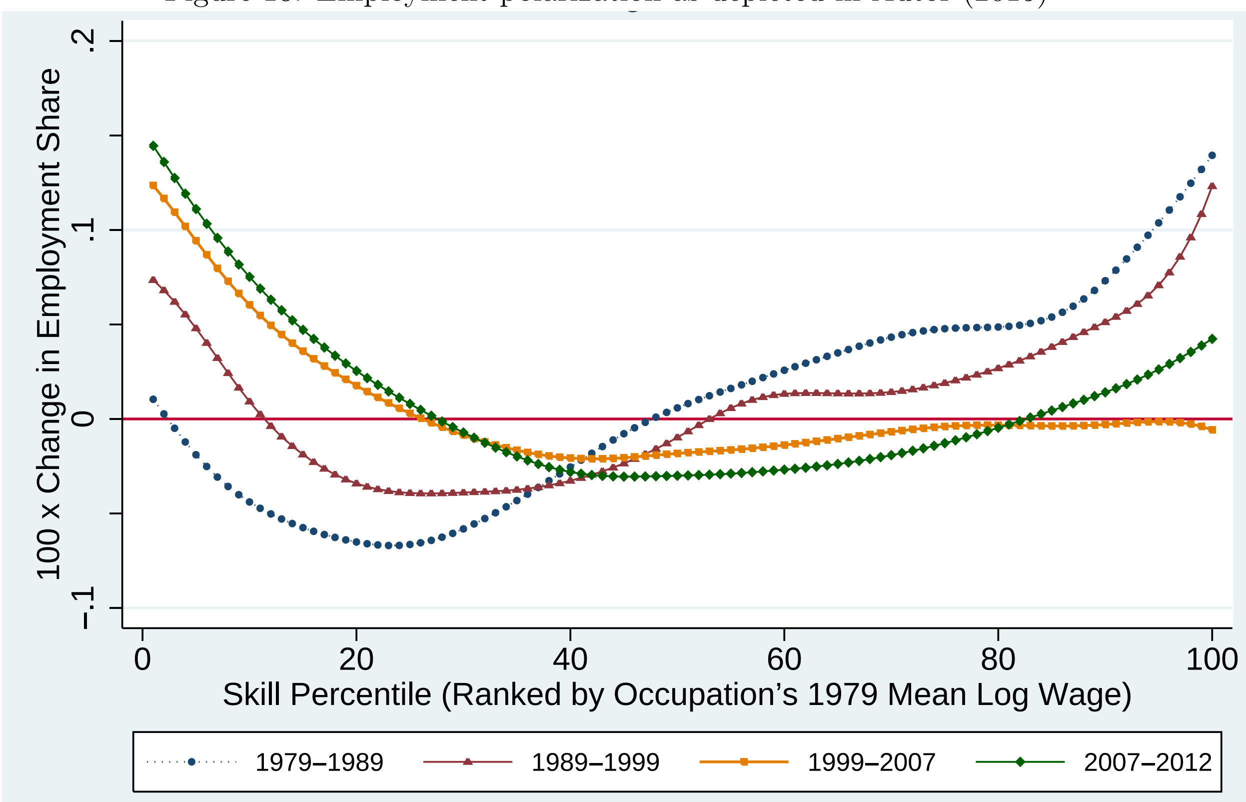
Note: Horizontal lines refer to percentiles of the wage distribution. 330 occupations.

Figure 17: Share of occupational wage percentile which is workers in fourth wage decile



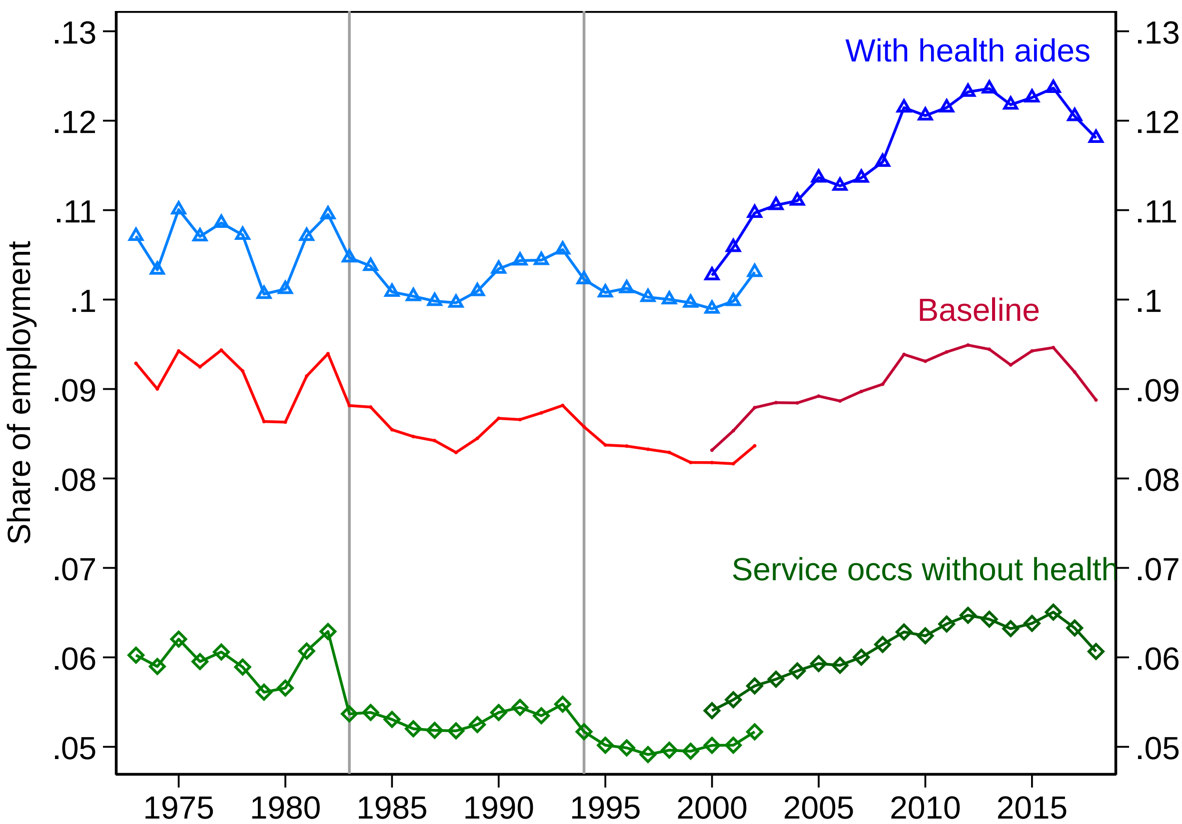
Note: 330 occupations.

Figure 18: Employment polarization as depicted in Autor (2015)



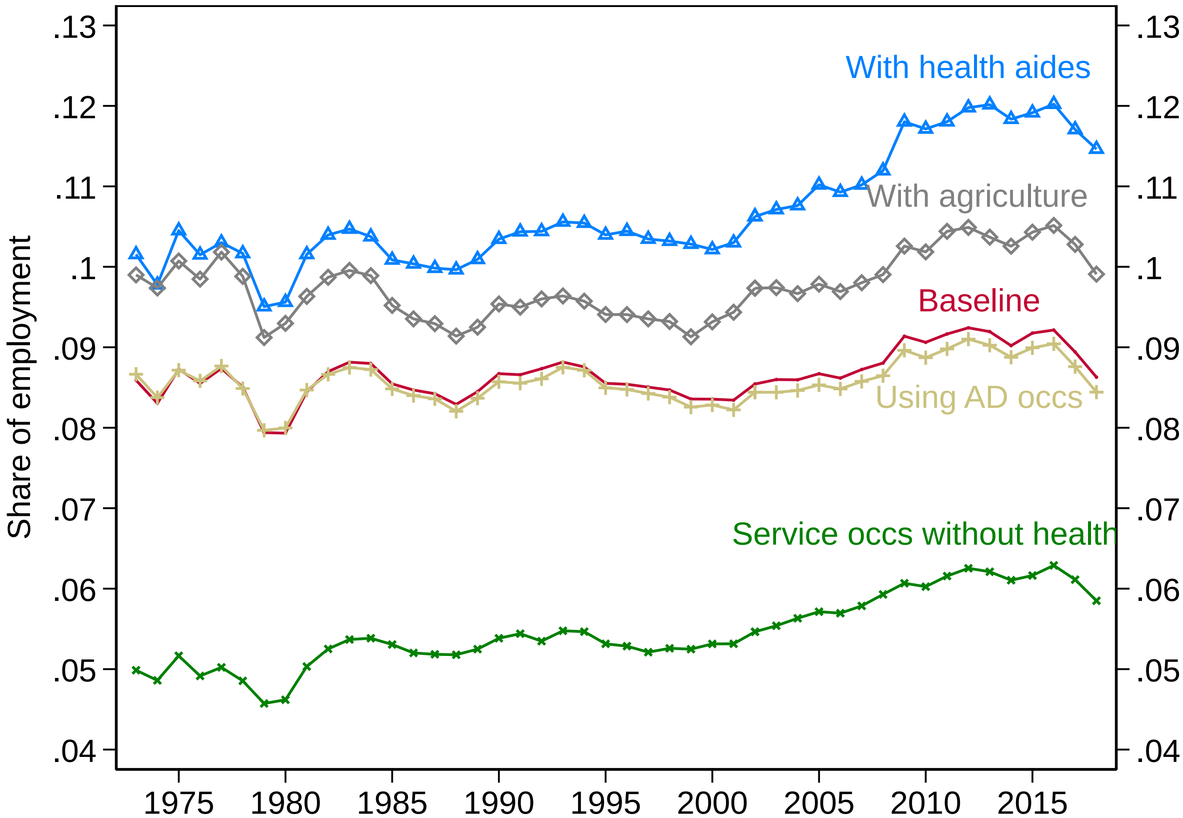
Source: Autor (2015a).

Figure 19: Shares of workers in lowest–paid occupations, 1973–2018



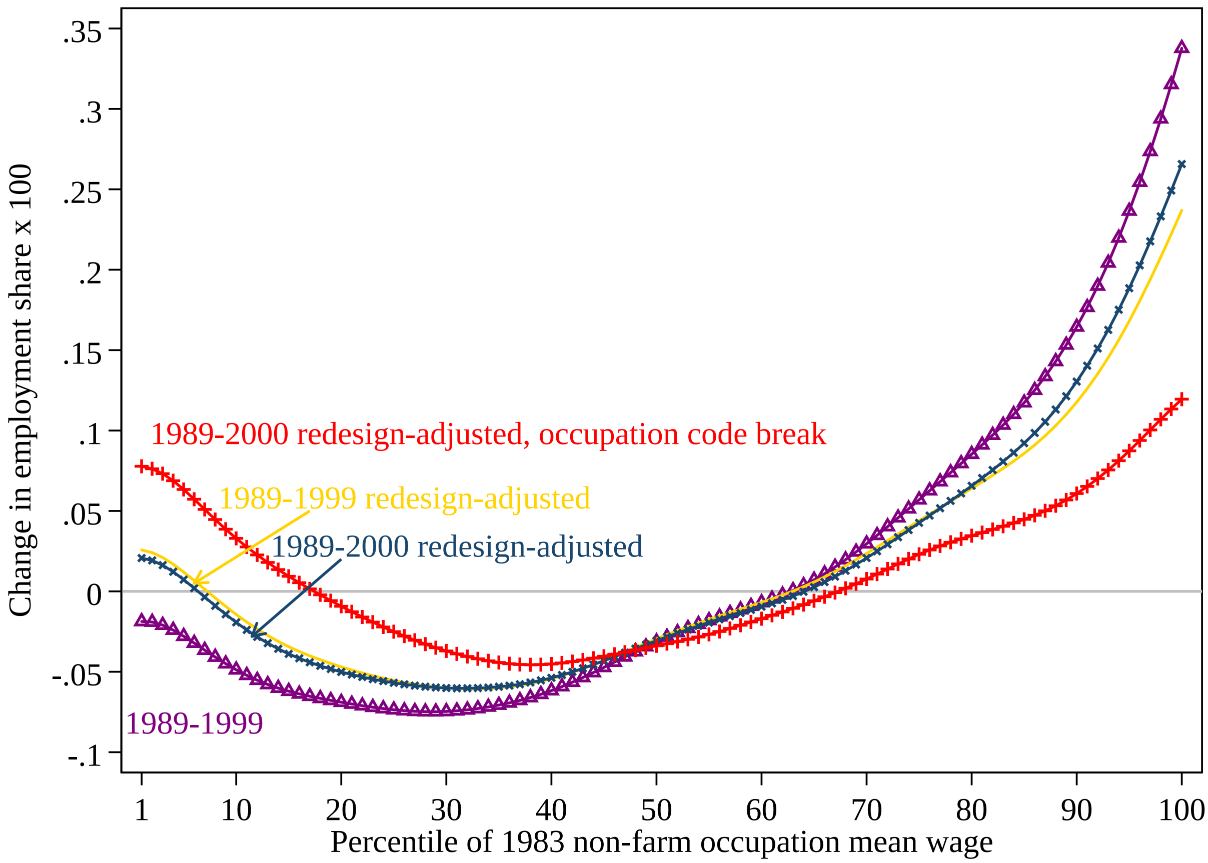
Note: The lowest–paid occupations are the bottom–ranked occupations by wage which employ 10% of workers in 1983. Service occupations are a subset of this group, defined as in Autor and Dorn (2013). The vertical lines indicate the occupation code break in 1983 and the CPS redesign in 1994.

Figure 20: Shares of workers in lowest–paid occupations, adjusted for series breaks, 1973–2018



Note: The lowest–paid occupations are the bottom–ranked occupations by wage which employ 10% of workers in 1983. Service occupations are a subset of this group. "AD occs" refers to occupations as ordered in Autor and Dorn (2013) based on annual earnings in the 1980 Census.

Figure 21: Change in employment share by occupation 1989–1999: reconciliation of CPS with the literature



Note: Adjustment for the 1994 CPS redesign consists of setting employment changes to zero in 1993–1994.

Figure 22: Change in employment share by occupation, 2000–2010 and 2011–2018

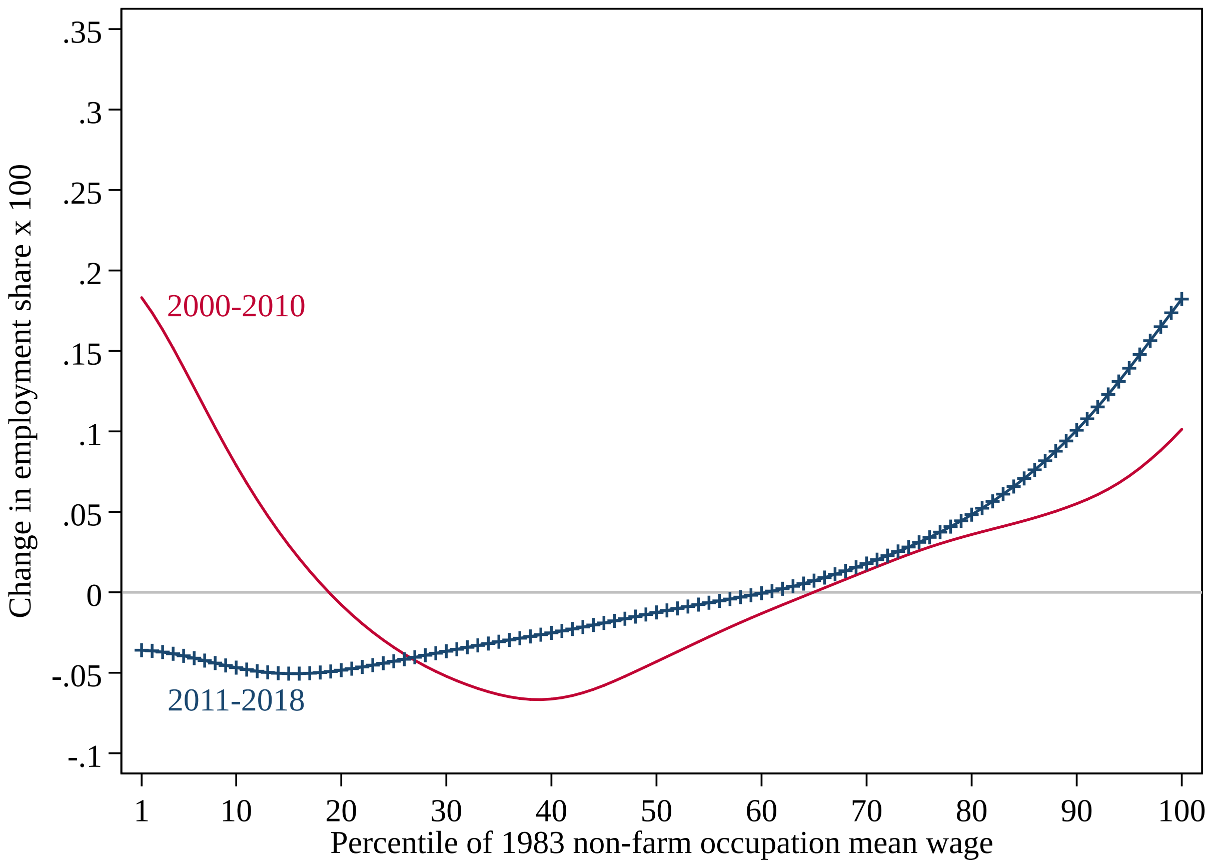
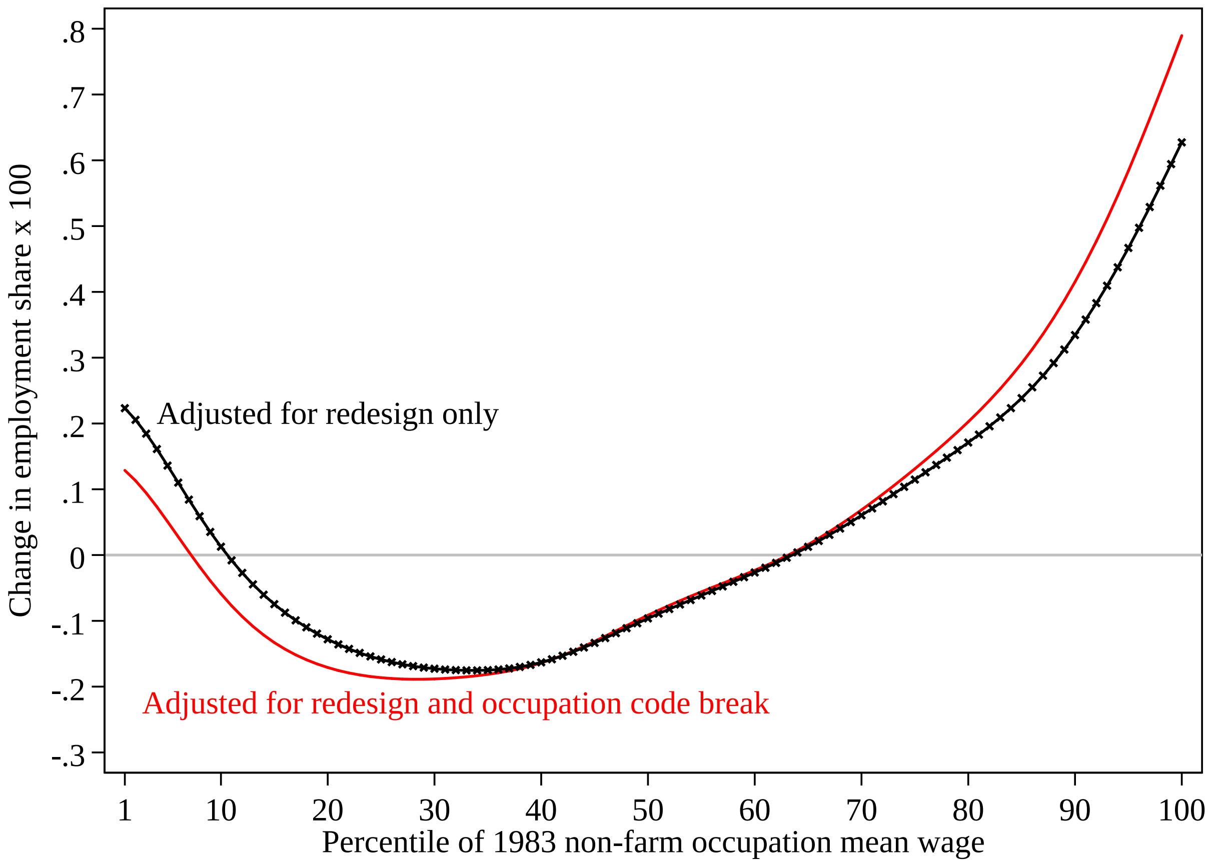
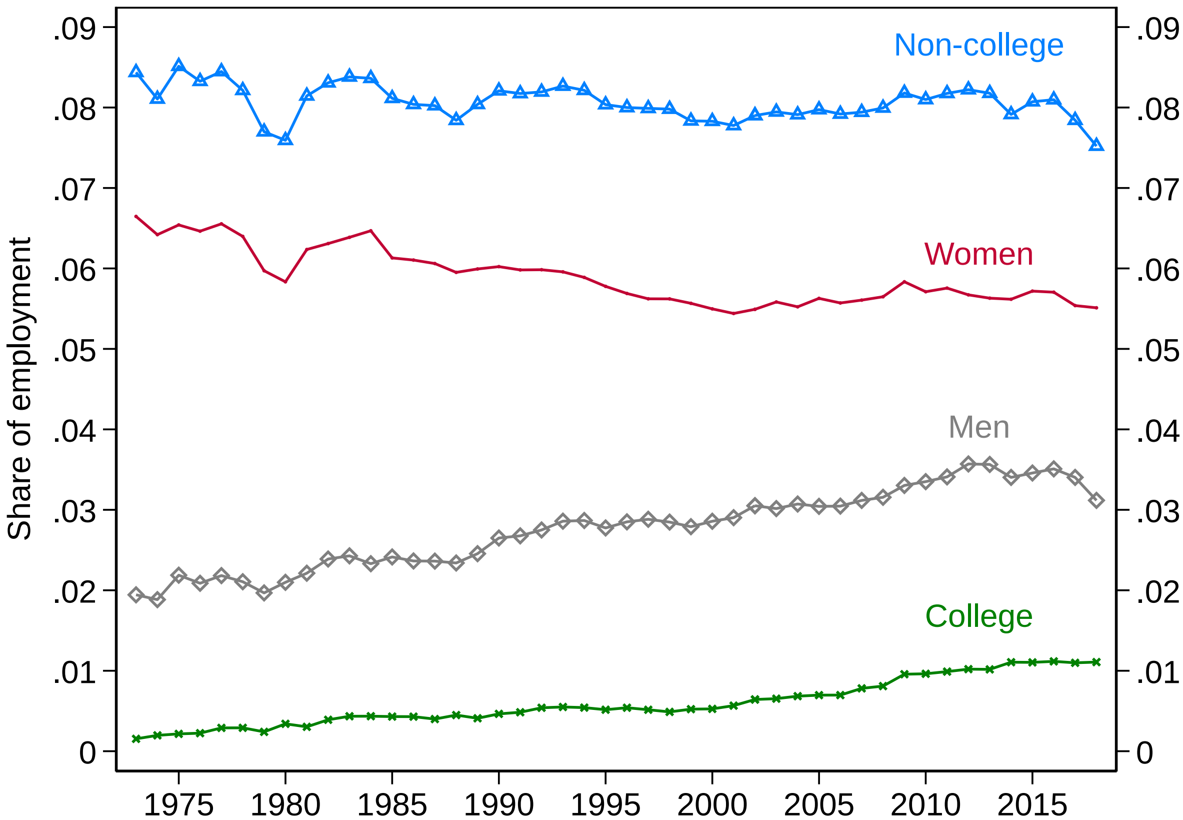


Figure 23: Change in employment share by occupation, 1983–2018



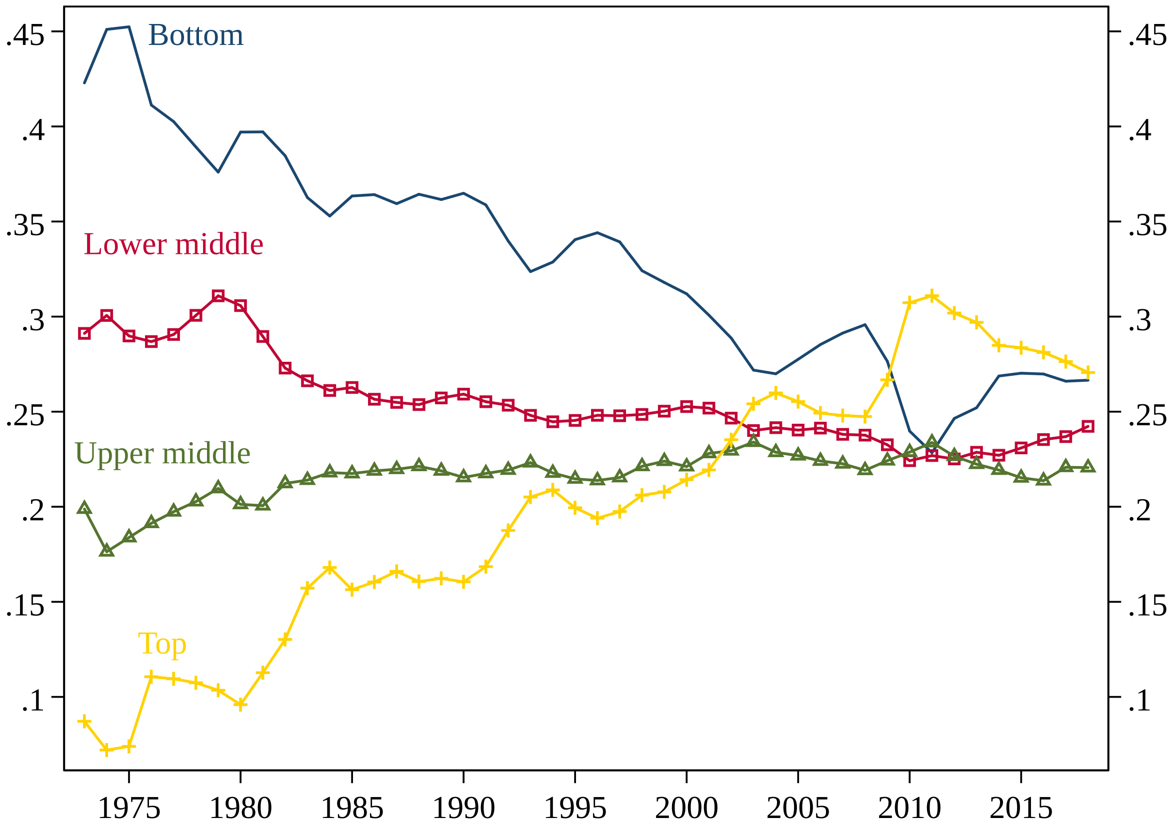
Note: Adjustment for the 1994 CPS redesign and 2000 occupation code break consists of setting employment changes to zero in 1993–1994 and 2002–2003.

Figure 24: Shares of subgroups of workers in lowest–paid occupations adjusted for series breaks, 1973–2018



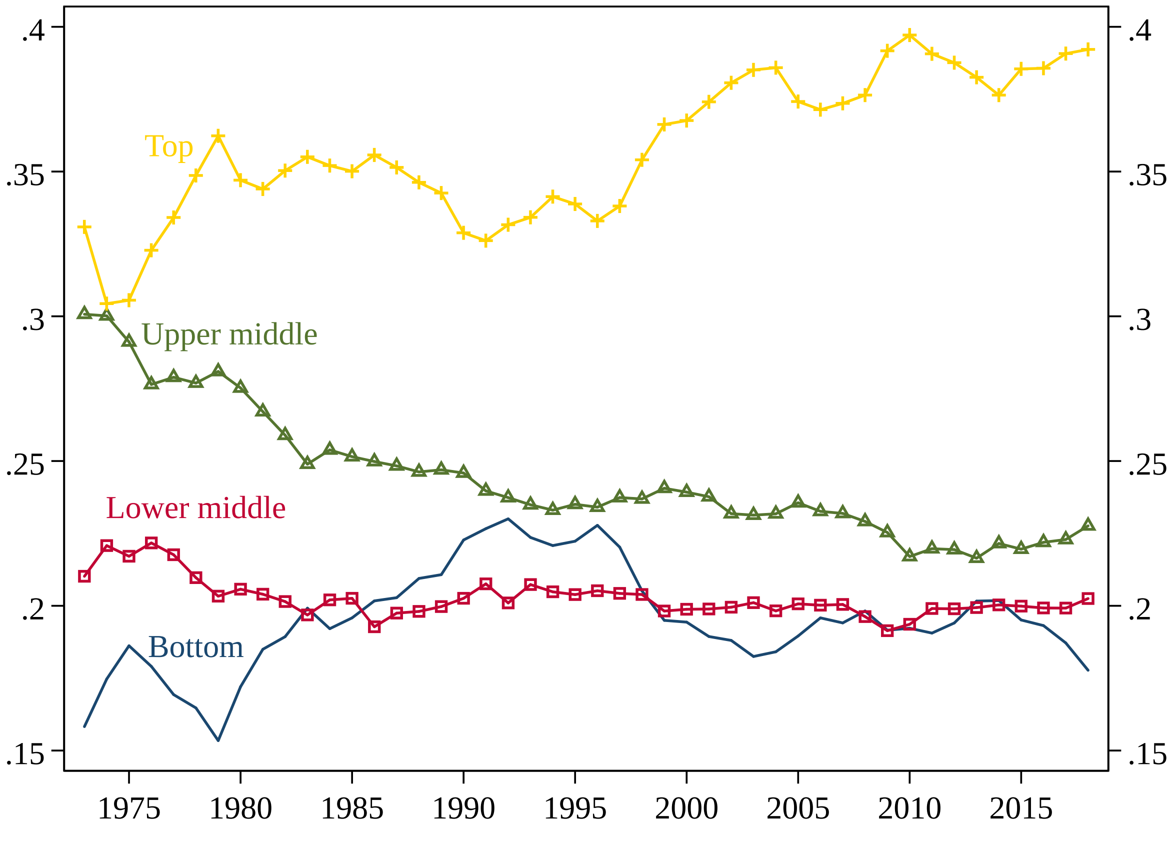
Note: The lowest–paid occupations are those employing 10% of workers in 1983. Women, men, college and non–college are subsets of this group.

Figure A1: Shares of women adjusted for business cycle, 1973–2018



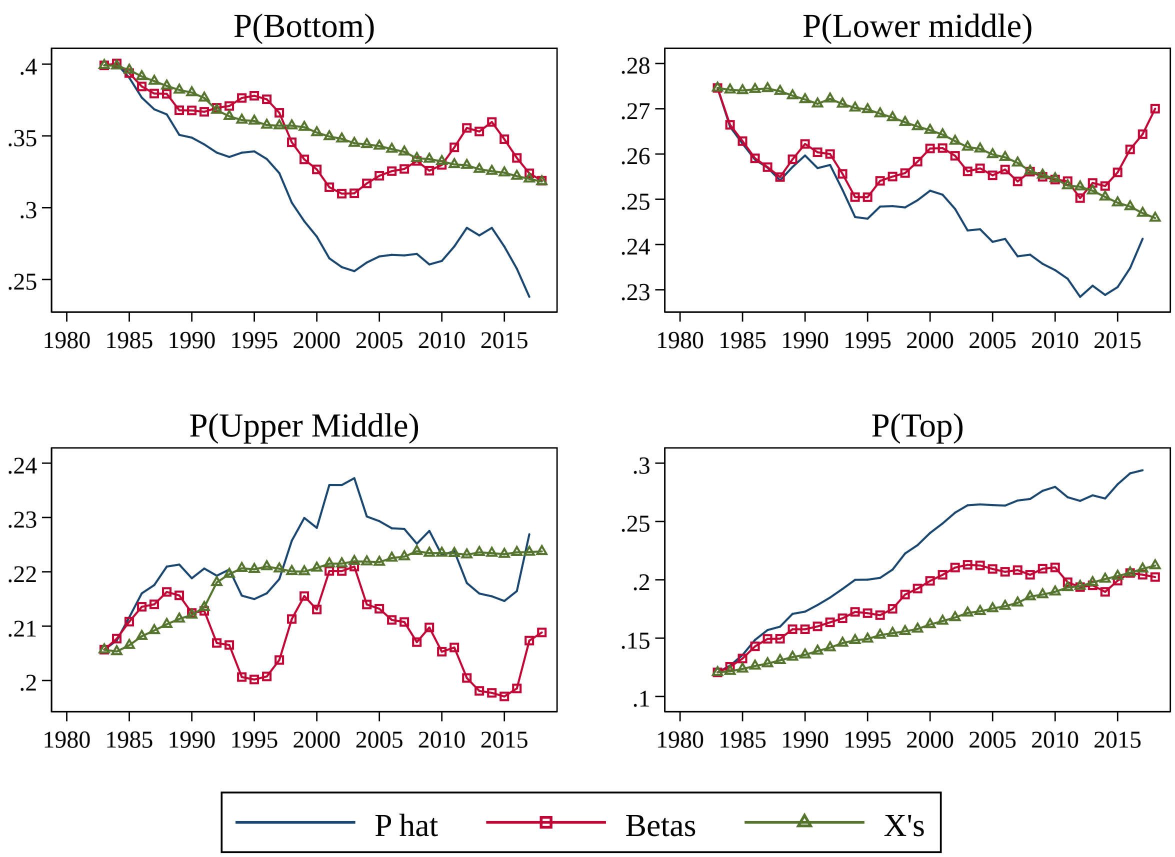
Note: Real wage bin thresholds are defined based on 1979 quartiles for pooled women and men.

Figure A2: Shares of men adjusted for business cycle, 1973–2018



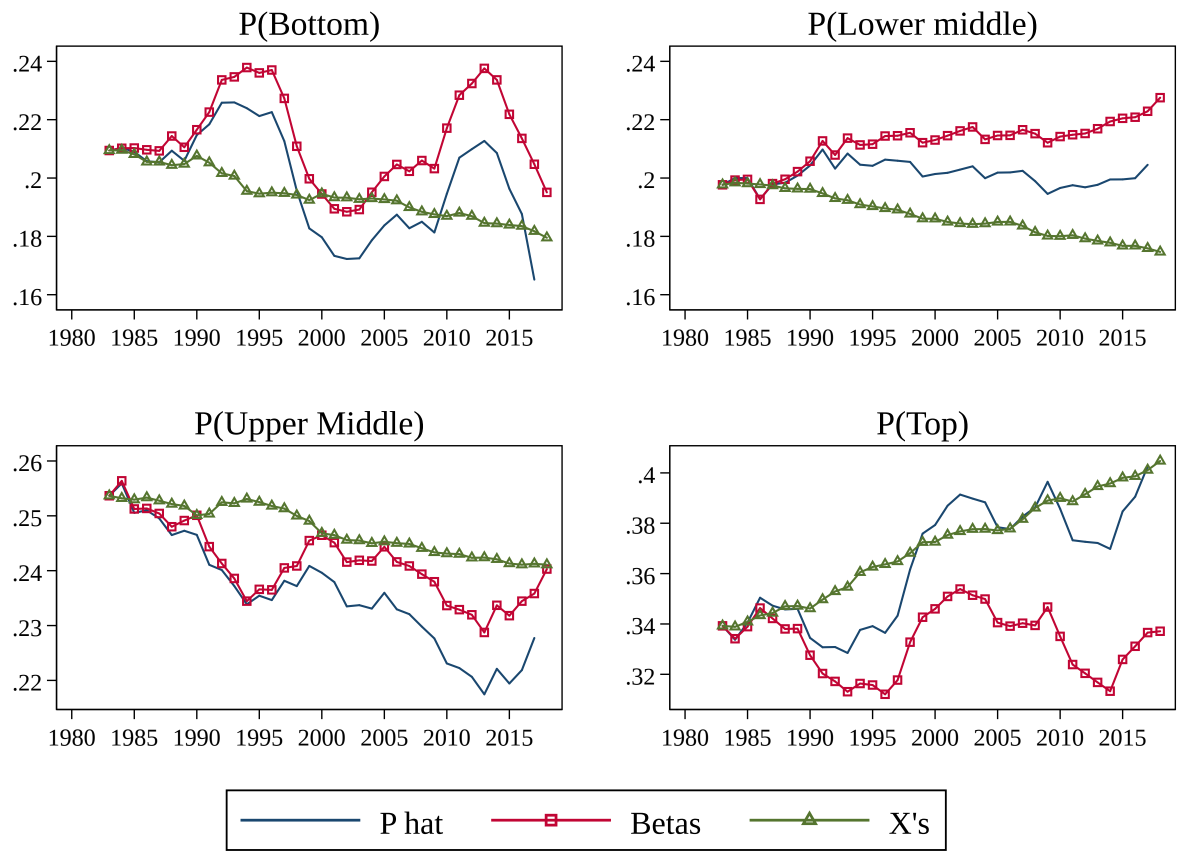
Note: Real wage bin thresholds are defined based on 1979 quartiles for pooled women and men.

Figure A3: Predicted shares and their components without occupation 1983–2018 – women



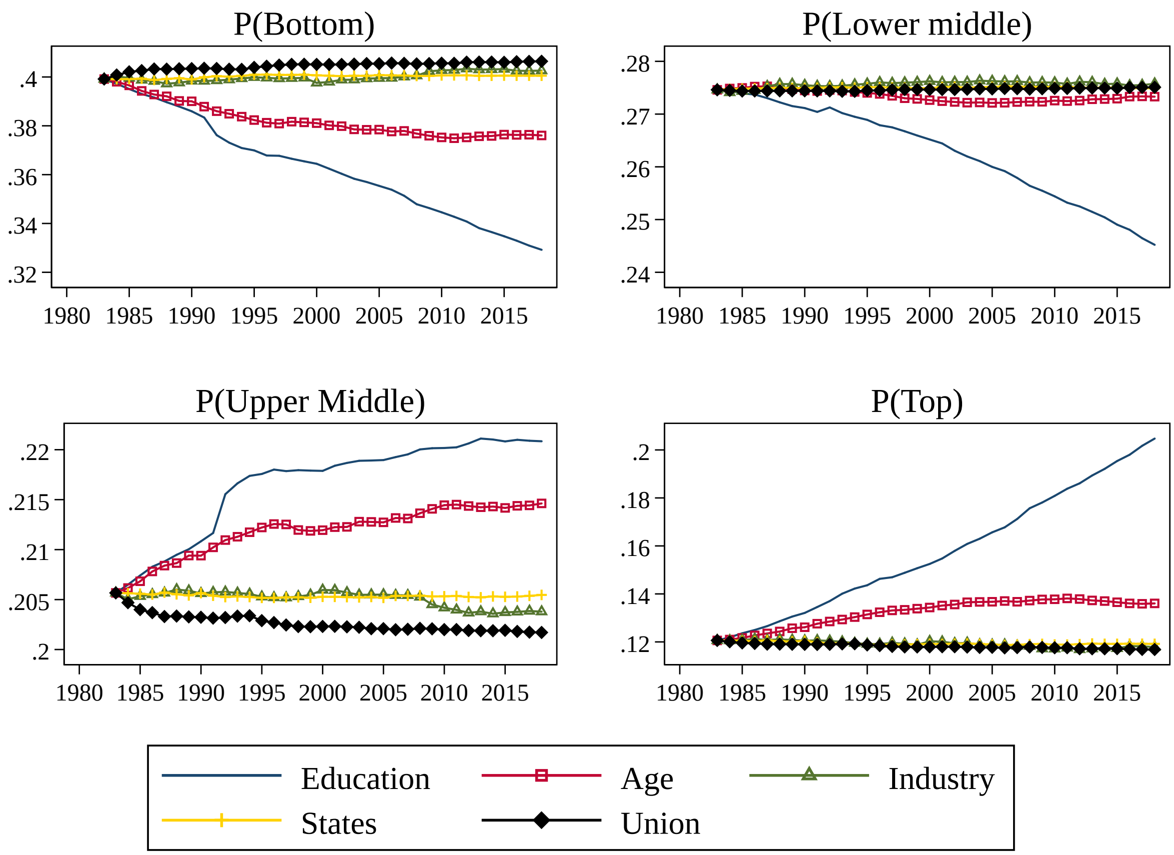
Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A4: Predicted shares and their components without occupation 1983–2018 – men



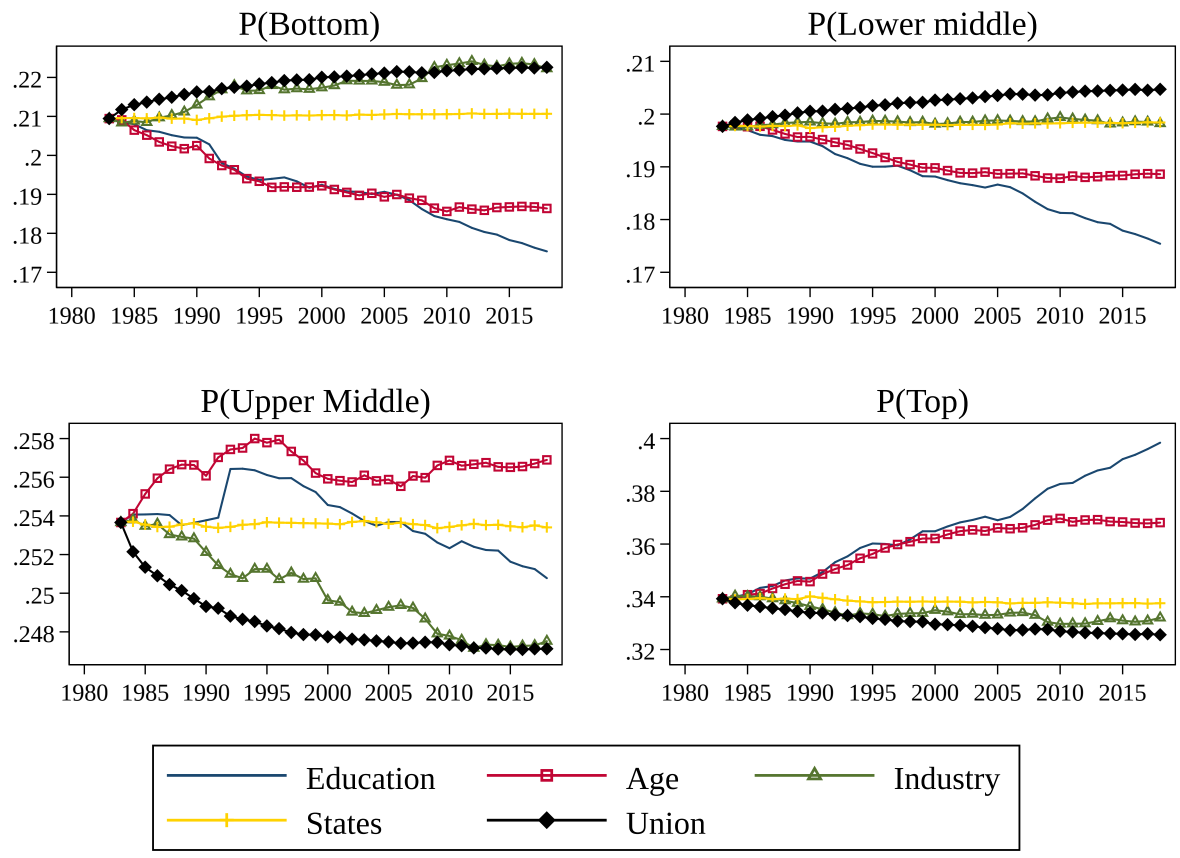
Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A5: Contributions of individual X's without occupation 1983–2018 – women



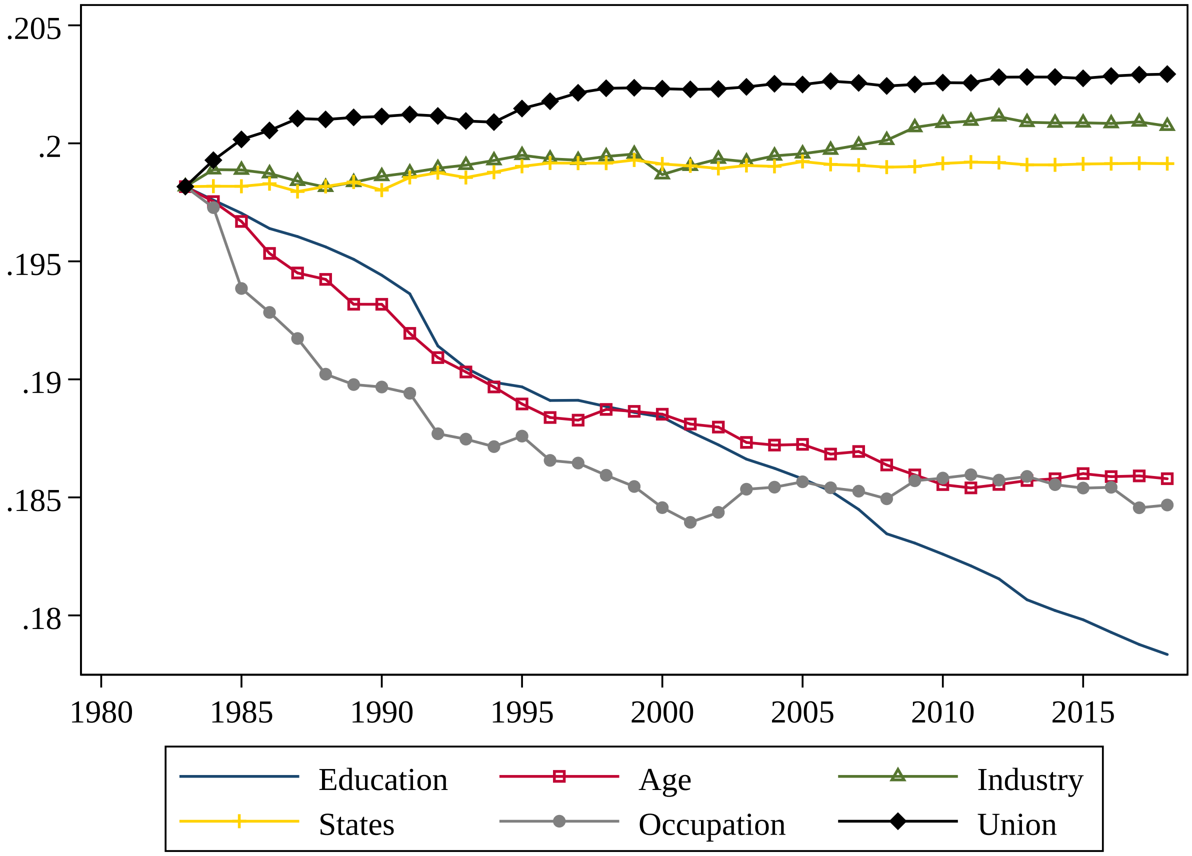
Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A6: Contributions of individual X's without occupation 1983–2018 – men



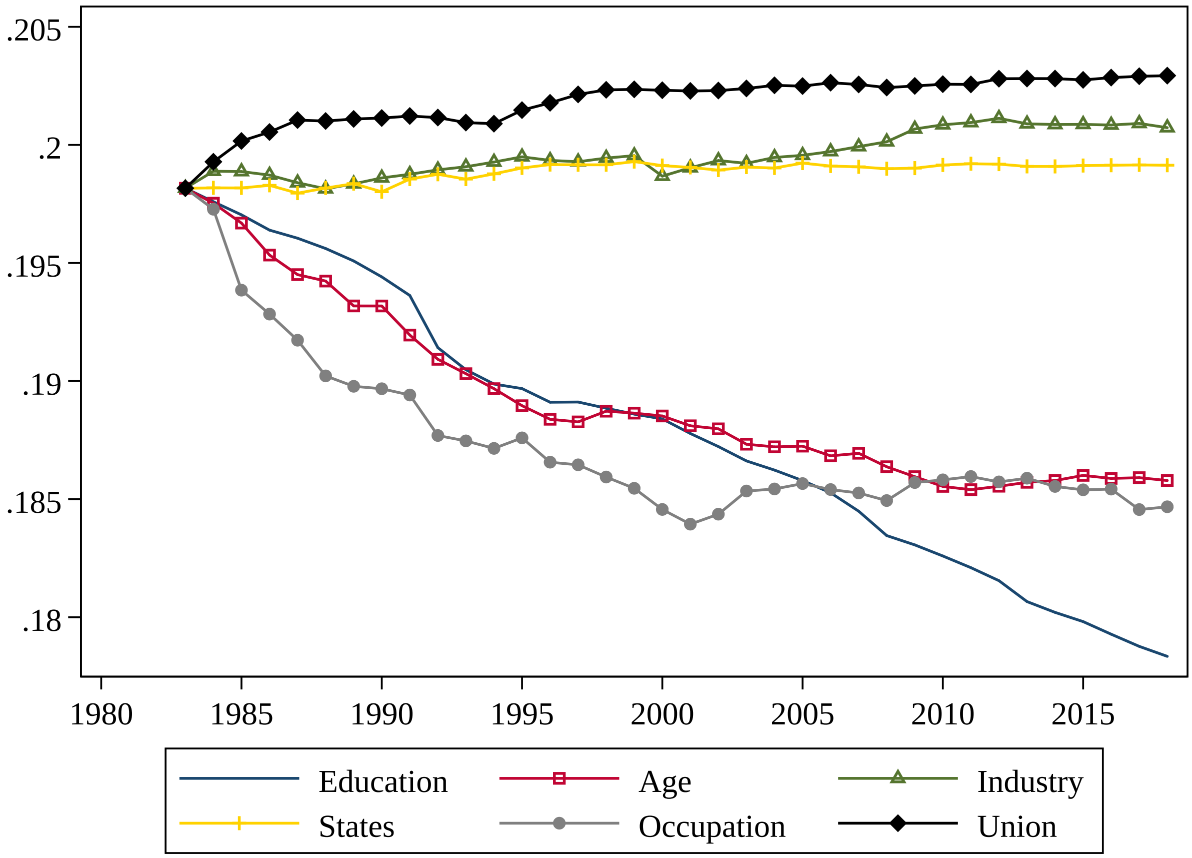
Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A7: Contributions of individual X's 1983–2018 bottom of ten bins – women



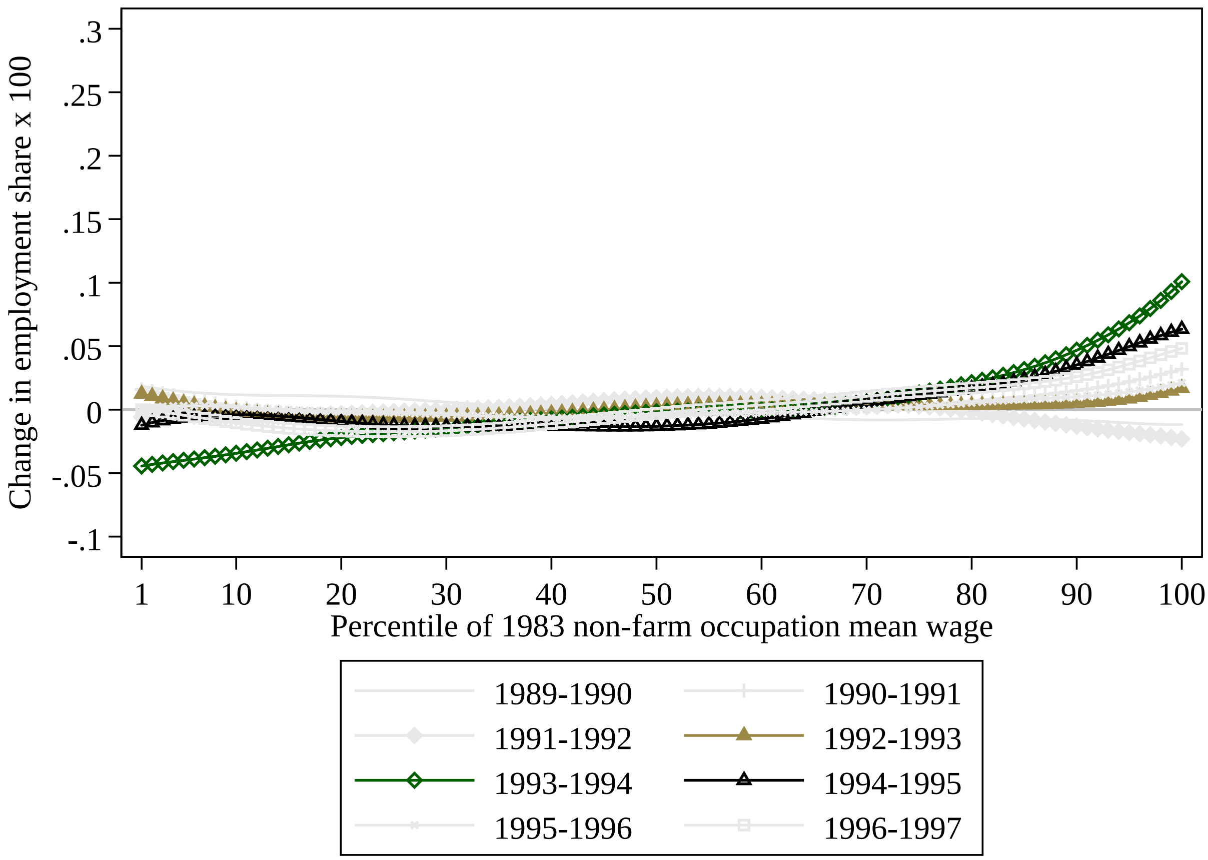
Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A8: Contributions of individual X's 1983–2018 bottom of ten bins – men



Note: Oaxaca decomposition based on education, age, state, union status, and industry.

Figure A9: Changes in employment share by occupation percentile for pairs of years in 1990s



Appendix Table 1: Means of age, education and union status

	Women					Men				
	1973	1983	1990	2008	2018	1973	1983	1990	2008	2018
Age 18-20	0.103	0.079	0.067	0.048	0.043	0.076	0.069	0.064	0.047	0.041
Age 21-24	0.144	0.134	0.105	0.089	0.089	0.125	0.125	0.106	0.089	0.085
Age 25-29	0.134	0.163	0.151	0.120	0.129	0.156	0.164	0.158	0.128	0.133
Age 30-34	0.100	0.142	0.151	0.108	0.118	0.129	0.149	0.158	0.119	0.127
Age 35-39	0.097	0.122	0.141	0.116	0.115	0.101	0.124	0.141	0.124	0.120
Age 40-44	0.099	0.101	0.130	0.121	0.106	0.102	0.099	0.122	0.123	0.109
Age 45-49	0.101	0.081	0.097	0.131	0.112	0.098	0.081	0.090	0.127	0.110
Age 50-54	0.097	0.073	0.070	0.120	0.110	0.092	0.077	0.070	0.110	0.104
Age 55-64	0.125	0.106	0.089	0.148	0.180	0.120	0.112	0.091	0.135	0.171
8 years school or fewer	0.096	0.042	0.033	0.020	0.018	0.140	0.071	0.060	0.038	0.029
9-12 years school	0.155	0.092	0.075	0.041	0.030	0.164	0.111	0.097	0.060	0.042
12 years school	0.473	0.455	0.422	0.280	0.237	0.381	0.388	0.387	0.321	0.306
13-15 years school	0.145	0.217	0.243	0.327	0.305	0.156	0.197	0.211	0.276	0.272
16 years school	0.089	0.121	0.143	0.224	0.262	0.090	0.131	0.144	0.203	0.231
Over 16 years school	0.043	0.073	0.084	0.109	0.149	0.070	0.101	0.101	0.101	0.121
Union member	0.147	0.152	0.129	0.117	0.101	0.327	0.255	0.197	0.137	0.113
Union coverage	0.000	0.035	0.024	0.014	0.013	0.000	0.031	0.021	0.012	0.011
Not member or covered	0.853	0.813	0.847	0.868	0.886	0.673	0.714	0.782	0.851	0.876
N	15,344	76,135	84,629	81,173	71,927	22,055	88,100	90,770	82,769	74,527

Appendix Table 2: Means of industries

	Women					Men				
	1973	1983	1990	2008	2018	1973	1983	1990	2008	2018
Agriculture/forestry	0.005	0.005	0.004	0.004	0.005	0.018	0.019	0.015	0.013	0.014
Mining/petroleum/coal	0.003	0.005	0.003	0.002	0.002	0.019	0.019	0.013	0.012	0.011
Construction	0.009	0.010	0.010	0.013	0.013	0.104	0.089	0.095	0.112	0.109
Furniture/wood	0.008	0.005	0.006	0.004	0.000	0.021	0.018	0.020	0.011	0.003
Non-metallic minerals	0.005	0.003	0.003	0.002	0.001	0.011	0.009	0.009	0.006	0.006
Metals	0.015	0.010	0.008	0.005	0.004	0.061	0.035	0.031	0.021	0.019
Machinery except electrical	0.013	0.014	0.012	0.004	0.004	0.041	0.039	0.034	0.015	0.013
Electrical machinery	0.031	0.023	0.017	0.011	0.007	0.029	0.026	0.023	0.020	0.015
Transportation equipment	0.010	0.011	0.012	0.009	0.009	0.044	0.039	0.037	0.027	0.027
Miscellaneous manufacturing	0.014	0.012	0.011	0.008	0.008	0.011	0.013	0.012	0.011	0.013
Food/beverage/tobacco	0.016	0.014	0.013	0.011	0.012	0.029	0.025	0.023	0.018	0.018
Textile/apparel/leather	0.060	0.036	0.025	0.006	0.004	0.020	0.014	0.012	0.004	0.004
Paper/printing	0.020	0.020	0.020	0.011	0.007	0.031	0.029	0.028	0.016	0.011
Chemicals	0.007	0.009	0.008	0.007	0.008	0.018	0.018	0.017	0.012	0.013
Plastics/rubber	0.007	0.006	0.005	0.003	0.002	0.010	0.010	0.009	0.006	0.005
Transportation/warehousing	0.015	0.021	0.026	0.026	0.028	0.053	0.061	0.063	0.068	0.067
Broadcasting/communication	0.019	0.017	0.015	0.012	0.008	0.014	0.017	0.015	0.019	0.016
Utilities/waste management	0.005	0.007	0.006	0.005	0.006	0.025	0.026	0.023	0.020	0.020
Wholesale trade	0.023	0.026	0.024	0.018	0.015	0.049	0.056	0.052	0.039	0.033
Retail trade	0.128	0.125	0.124	0.115	0.109	0.102	0.098	0.102	0.111	0.108
Finance	0.037	0.048	0.046	0.043	0.037	0.015	0.020	0.021	0.028	0.029
Insurance/real estate	0.035	0.042	0.046	0.039	0.039	0.023	0.026	0.028	0.024	0.028
Private households	0.032	0.018	0.013	0.011	0.010	0.001	0.003	0.002	0.001	0.001
Business services	0.021	0.032	0.045	0.044	0.051	0.018	0.035	0.049	0.064	0.079
Repair	0.003	0.002	0.002	0.003	0.003	0.016	0.015	0.017	0.019	0.020
Personal services	0.032	0.029	0.033	0.030	0.032	0.010	0.014	0.017	0.015	0.014
Arts/entertainment	0.006	0.009	0.010	0.019	0.020	0.008	0.011	0.011	0.022	0.023
Hospitals	0.082	0.086	0.077	0.079	0.081	0.017	0.022	0.020	0.022	0.024
Healthcare except hospitals	0.049	0.065	0.073	0.107	0.120	0.006	0.008	0.010	0.022	0.026
Educational services	0.153	0.126	0.124	0.148	0.142	0.059	0.060	0.055	0.057	0.059
Social assistance	0.019	0.024	0.030	0.035	0.036	0.010	0.006	0.007	0.006	0.006
Other professional services	0.023	0.035	0.043	0.059	0.063	0.018	0.029	0.031	0.049	0.054
Public administration	0.043	0.048	0.050	0.050	0.050	0.072	0.060	0.059	0.056	0.056
Food services	0.051	0.058	0.056	0.061	0.067	0.018	0.033	0.039	0.052	0.055
N	15,344	76,135	84,629	81,173	71,927	22,055	88,100	90,770	82,769	74,527

Appendix Table 3: Oaxaca decomposition of women's share in top and bottom wage groups

	1983-1990		1990-2008		2008-2018	
	Bottom	Top	Bottom	Top	Bottom	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
ΔP	-0.719***	0.744***	-0.450***	0.536***	-0.299***	0.247***
	(0.035)	(0.025)	(0.013)	(0.011)	(0.022)	(0.023)
Δβ	-0.388***	0.453***	-0.231***	0.231***	-0.192***	-0.004
	(0.030)	(0.023)	(0.013)	(0.012)	(0.020)	(0.020)
ΔX	-0.332***	0.292***	-0.219***	0.306***	-0.128***	0.251***
	(0.020)	(0.015)	(0.009)	(0.009)	(0.012)	(0.014)
Panel B						
Age	-0.108***	0.072***	-0.061***	0.064***	-0.005	-0.010**
	(0.006)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Education	-0.113***	0.101***	-0.133***	0.149***	-0.106***	0.183***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
Industry	0.014**	-0.012**	0.015***	-0.018***	0.008**	-0.014***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Union	0.056***	-0.029***	0.007***	-0.006***	0.009***	-0.010***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
State	-0.004	-0.000	0.002*	-0.005***	0.000	-0.001
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Occupation	-0.177***	0.160***	-0.050***	0.121***	-0.024***	0.103***
	(0.011)	(0.010)	(0.007)	(0.007)	(0.007)	(0.008)
Observations	160,764		165,802		153,100	

Note: Contributions in percentage points per year. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 4: Oaxaca decomposition of men's share in top and bottom wage groups

	1983-1990		1990-2008		2008-2018	
	Bottom	Top	Bottom	Top	Bottom	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
ΔP	0.076**	-0.068**	-0.165***	0.288***	-0.089***	0.135***
	(0.028)	(0.032)	(0.011)	(0.013)	(0.022)	(0.027)
Δβ	0.067***	-0.103***	-0.064***	0.064***	-0.052**	0.012***
	(0.024)	(0.028)	(0.011)	(0.013)	(0.020)	(0.024)
ΔX	0.008	0.035*	-0.100***	0.223***	-0.037**	0.124
	(0.016)	(0.019)	(0.008)	(0.010)	(0.011)	(0.016)
Panel B						
Age	-0.082***	0.073***	-0.068***	0.102***	-0.017***	0.009
	(0.007)	(0.007)	(0.003)	(0.003)	(0.004)	(0.005)
Education	-0.050***	0.060***	-0.070***	0.102***	-0.066***	0.123***
	(0.004)	(0.006)	(0.003)	(0.004)	(0.004)	(0.006)
Industry	0.039***	-0.029***	0.019***	-0.015***	0.021***	-0.023***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)
Union	0.104***	-0.116***	0.024***	-0.045***	0.013***	-0.028***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.001)	(0.003)
State	-0.004	0.013***	0.002*	-0.004**	-0.001	-0.001
	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
Occupation	0.001	0.030**	-0.008	0.082***	0.013**	0.044***
	(0.008)	(0.011)	(0.005)	(0.007)	(0.006)	(0.009)
Observations	178,870		173,539		158,934	

Note: Contributions in percentage points per year. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.