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Job Polarization and the Declining Fortunes of the Young: Evidence from the United Kingdom

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Abstract

This paper uses a life-cycle framework to document new stylized facts about the nexus between job polarization and earnings inequality. Using quarterly labor force data for the UK over the period 2000-2018, we find clear life-cycle profiles in the probability of being employed within each occupation type and wages earned therein. Cohort plots and econometric analysis suggest that labor market outcomes and prospects have gradually worsened for the young. These adverse trends are particularly significant for low-skill women: estimated cohort effects point to a fall in wages within each occupation as well as a lower propensity of being employed in abstract-task occupations. We also find evidence of general occupational downgrading in the UK, with more educated workers taking up fewer high-skill occupations than they did in the past. Our analysis informs the policy debate over appropriate measures needed to reduce skill mismatches and alleviate labor market transitions.

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I. Introduction

During recent decades, labor markets in many advanced economies have become increasingly polarized as the share of employment in middle-wage occupations has declined. This "hollowing out" of the middle of the wage distribution has been linked to the disappearance of routine occupations—jobs with a higher share of tasks performable through a set of easily codified rules. Potential causes include progress in automation technologies that substitute for labor (Autor et al., 2003; Goos and Manning, 2007) and offshoring due to globalization (Autor and Dorn, 2013). The declining share of employment in routine jobs and growing wage polarization are also associated with higher earnings inequality (Acemoglu and Autor, 2011). Who is the loss of routine job opportunities affecting most acutely? Are young workers worse off than older generations? Across cohorts, is this driven by differences in the composition and propensity of specific demographic groups to work in routine and other jobs?

This paper uses a life-cycle framework to examine the nexus between job polarization and earnings inequality in the United Kingdom (UK). We focus on cohort-specific changes in the propensity of employment in a given occupation type and the expected wages therein for different groups of workers. Specifically, we document new stylized facts about changes in routine occupations for successive cohorts of college and non-college educated (alternatively high- and low-skill) male and female workers in the UK. Organizing the data by cohorts allows us to examine whether labor market outcomes and prospects have worsened for the young.

Using the UK quarterly Labour Force Survey (LFS), we show that job polarization partly drives the widening wage gap for young and prime-age workers since the 2000s. However, polarization itself takes place through different channels. At the aggregate level, changes in labor market composition—particularly the increase in the proportion of the working-age population with a college degree—has impacted labor market outcomes. This is because high-skill workers receive higher average wages within each occupation. Additionally, high-skill workers have a greater likelihood of being employed in higher-earning abstract occupations (such as management, professional, and some technical jobs).[1] We show that the rising share of workers with a university education accounts for most of the decline in routine jobs over the past 20 years.

Our analysis also uncovers important differences across specific demographic groups (gender, education, age). Although job polarization between 2001 and 2018 has taken place for all low-skill workers (men and women without a college degree), the share of employment in abstract occupations has actually declined among the high-skill labor force. This pattern of "occupational downgrading" is consistent with findings for the United States (US) (Beaudry et al., 2014). Furthermore, for each gender-education group, there are clear life-cycle profiles in the propensity of being employed within each occupation type. Generally, older workers are more likely to be employed in abstract occupations than in routine jobs. Synthetic cohort plots,

[1] These abstract occupations typically require flexibility, creativity, problem-solving, or human interaction skills (see Autor et al., 2003, for a classification of abstract and routine jobs).

however, show that these profiles have shifted over time and across cohorts, suggesting that younger workers are worse off than previous generations. Low-skill women, particularly young women just entering the workforce, are most affected by job polarization. This runs counter to findings for the US, where low-skill, prime-age males have experienced the sharpest drop in the propensity for routine employment (Cortes et al., 2017).

To disentangle intergenerational differences from aggregate trends and the life-cycle component, we use a linear probability model to estimate age, cohort, and year effects of the propensity to be employed in each occupation type. We then apply the same estimation to wages to examine inter-cohort disparities in earnings within each occupational group. This reduced-form approach allows us to conduct a set of intuitive counterfactual exercises to decompose the wage gap between younger and older workers arising from year, cohort, and labor force composition effects.

The econometric analysis corroborates the stylized facts documented above while providing a more nuanced picture across demographic groups. First, we find that young low-skill workers have experienced a worsening in their earnings prospects compared not only to high-skill workers but also to previous generations of low-skill workers. These adverse trends are particularly large for women: estimated cohort effects point to a fall in wages within each occupation as well as a lower propensity of being employed in abstract occupations. Second, high-skill workers have witnessed a lower likelihood of obtaining employment in abstract occupations and a pronounced slowdown in wage growth since the Great Recession. In previous literature on changes in the wage structure, movements of employment and wages in the same direction are seen as evidence of labor demand shifts (e.g., Katz and Murphy, 1992; Autor, Katz, and Kearney, 2008).

Counterfactual exercises show that the adverse labor market prospects captured by cohort effects account for over half the increase in wage inequality between young and prime-age workers over the past two decades. This effect offsets the mitigating impact of the higher educational attainment of younger generations. Moreover, these differences have a quantitatively large impact on workers' earnings over the course of their entire careers. We estimate that females without a college education born in 1990-1994 can expect 15 percent lower lifetime earnings relative to workers born during the 1960's. We also find that young high-skill workers could suffer a large fall in lifetime earnings because the adverse impact of the aggregate wage slowdown observed since 2008 could persist throughout their careers.

We discuss three recent trends that could underlie the negative cohort effects for younger workers. First, evidence suggests that the returns to education in the UK are very heterogeneous, depending on the type of degree and subject, and have fallen over time (Abel et al., 2016, Belfield et al., 2018). A second trend relates to the large and persistent rise in the share of involuntary part-time employment among young workers since 2008, potentially indicating higher "underemployment". Finally, we show that occupational polarization has been closely aligned with the shifting industrial composition of the UK economy over the last few decades.

Our paper is related to several strands of literature. A growing body of work has examined the impact of routine-biased technical change (RBTC) across different demographic groups (see Cortes et al., 2016; Bussolo et al., 2018), highlighting the diverging fortunes of "losers" and "winners". For instance, while de-industrialization in the US has largely affected low-skill males (Cortes, 2016), recent papers find that, in many countries, women work in jobs that are most vulnerable to automation (e.g. Brussevich et al., 2018).[2] Our paper is also related to studies that examine the multi-faceted nature of polarization in the UK (Salvatori, 2018; Cristini et al., 2017; Nedelkoska and Quintini, 2018; Montresor, 2019). Both Salvatori (2018) and Montresor (2019) - the latter focusing on geographic heterogeneity- conclude that job polarization occurred only among non-college graduates while the rise in university attendance accounted for most of the growth in abstract jobs. Relative to these works, our contribution is to examine job polarization trends from the lens of workers' life-cycles and inter-generational inequality, uncovering key differences across cohorts and gender. The inter-generational perspective provides further nuances to the debate on the "losers" and "winners" of structural change. For instance, in the UK it is not just low-skilled females who have witnessed the most significant worsening in labor market earnings, but young low-skill females just entering the workforce.

Several papers document the disproportionately adverse impact of the 2008 Great Recession on labor market outcomes for young workers (Elsby et al. 2010; Boeri et al. 2016; Hur 2018; Chen et al. 2018). Although the wage differential between young and old workers has been widening since the early 2000's, this gap rose substantially after the Great Recession. Oreopulos et al. (2012) and Leombruni et al. (2015) provide evidence of large and long-lasting negative effects for labor market entrants during a recession, consistent also with our findings for the UK. However, by framing the analysis from a cohort perspective, we show that part of the slowdown in earnings for young workers preceded the crisis. In this regard, our finding is consistent with Beaudry et al. (2014), who document that the employment share of abstract occupations in the US has stagnated for new cohorts of college-educated workers since 2000. While their study focuses exclusively on high-skill workers, our analysis encompasses all workers disaggregated by gender and education level.

Finally, our analysis informs the policy debate over appropriate measures to alleviate labor market transitions. This debate is currently of high relevance in the UK, as robust explanations for the large slowdown in wage growth (Gregg et al., 2014; Bell and Blanchflower, 2018a) and the protracted productivity slowdown known as the "productivity puzzle" (Blundell et al., 2014, Pessoa and Van Reenen, 2014) remain elusive. Furthermore, several studies have noted the growing inter-generational inequality in wealth accumulation and homeownership.[3] Since income and expected lifetime earnings underpin most economic decisions, focusing on the

[2] Some studies suggest that high-skilled females could possess a comparative advantage in abstract occupations, as they may more effectively combine cognitive and interpersonal skills (Bhalotra and Fernández 2018, Cortes et al. 2018, Ngai and Petrongolo 2017, Goldin 2006).

[3] See Resolution Foundation (2018) and references therein.

forces driving labor market inequalities can also shed light on disparities in other socioeconomic outcomes.

The rest of this paper is structured as follows. Section II describes the data and the occupational categorization we apply, discusses overall job polarization trends, and presents evidence on job polarization across worker cohorts disaggregated by gender and education. Section III presents the estimation of age, year, and cohort effects in employment propensities and wages using a linear regression model. In Section IV, we carry out a set of counterfactual exercises to quantify the relevance of the cohort effects for earnings inequality across ages and for workers' expected lifetime incomes. Section V discusses structural developments that could potentially underlie the bleaker labor market prospects for recent cohorts. Section VI concludes.

II. Descriptive Evidence

A. The Data

We use data from the UK Labour Force Survey (LFS), available at quarterly frequency from the mid-1990s. Our main sample focuses on employed workers aged 21 to 65 over the period 2001:Q2-2018:Q4.[4] The data is comprised of repeated cross-sections in each survey that are used to construct synthetic cohorts of workers.[5] The second data source comprises the categorization of occupations based on their "task content" as proposed by Cortes et al. (2016). We merge these categorical definitions of occupations with occupational classifications for the UK. While Cortes et al. (2016) classify occupations along two orthogonal dimensions, routine vs. non-routine and manual vs. abstract, we combine their two routine categories (manual and abstract) into a single group and define the two non-routine groups as simply manual and abstract. This gives us three possible categories for each occupation: abstract, manual, and routine.[6] Although this grouping may appear generic, it captures the more detailed information given by alternative measures of task content, such as the Routine Task Index (RTI) developed by Autor and Dorn (2013) and other methods (see Annex 2).[7]

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[4] Although the LFS contains occupation and wage information since 1997, the switch from the 1990 Standard Occupational Classification (SOC1990) to the updated SOC2000 in 2001 creates a discontinuity in the analysis. Therefore, the analysis considers the period 2001:Q2-2018:Q4 for which the occupations are classified using SOC2000.

[5] See Deaton and Paxson (1994) and Attanasio (1998) for a discussion of synthetic cohort analysis.

[6] We use a cross-walk between SOC2000 and the International Labour Organization's ISCO08 to merge the UK data with the occupational categorization and task-content data, which are based on US classifications. See Annex I for details.

[7] A further caveat, as pointed out by Bhalotra and Fernández (2018), is that task-based indices and categorizations constructed on US occupations may not be fully representative of the task content of occupations in another country. For a deeper analysis of the numerous combinations of skills involved in different occupations in the UK see Nedelkoska and Quintini (2018).

B. Job Polarization in the UK: 2001-2018

The Aggregate Picture

The starting point for our analysis is the earnings gap for young relative to prime-age and older workers. **Figure 1** plots the average hourly wage of all workers divided into three broad age groups: 21 to 34 years (young), 35 to 49 (prime-age), and 50 to 65 (old).[8] The wage differential grew from GBP 1.9 in 2001 to GBP 3.1 in 2018, or from 17 to 27 percent of the young's average wage in relative terms. The wage gap has widened since 2001, indicating that this phenomenon preceded the Great Recession. Starting in 2008, however, wages of younger workers have fallen substantially and have yet to reach their pre-recession peak. Older workers, on the other hand, have witnessed a protracted wage slowdown but not as sharp a decline.

Over the same period, there has been a pronounced employment shift away from routine occupations. As can be seen from **Figure 2**, which reports the share of total employment by occupation, employment share in routine occupations has fallen by more than 10 percentage points from 2001 to 2018. Employment in abstract occupations has grown by almost the same magnitude, while the share of manual jobs has remained effectively constant.

Job Polarization Across Gender and Education

Declining employment in routine jobs is heterogenous across groups of workers. **Table 1** reports the share of workers in routine, abstract, and manual jobs by gender, with and without a college education (denoted college and non-college educated, respectively, or high- and low-skill). Two key observations stand out. First, college-educated workers are more likely to be employed in abstract jobs while non-college educated workers are likely to be in routine occupations. Second, the share of college-educated workers rose by 15.5 percentage points over the same period, with females accounting for most of the increase. This suggests that a change in the composition of the labor force towards workers with higher educational attainment underpins part of the aggregate reallocation of labor into abstract jobs.

While the importance of this compositional shift has been noted previously, **Table 1** and **Figure 3** indicate that there have also been marked changes in the occupational distribution within each demographic group. For college-educated workers, the share of employment in abstract jobs has declined, while their share in routine jobs has slightly increased. This pattern is reversed for non-college educated workers who have experienced a declining employment share in routine occupations. Non-college females stand out as their routine share has declined from 55 to 45 percent in less than 20 years. Finally, the share of both manual and abstract jobs

[8] Wages are reported in 2010 prices by adjusting the nominal value by the UK Consumer Price Index at quarterly frequency.

increased for non-college females, indicating a reallocation of labor into both high- and low-skill occupations.[9]

To investigate the relative importance of the within-group trends and compositional changes we apply a shift-share analysis from 2001 to 2018, as in Cortes et al. (2017). The change in the total employment share of an occupation group is decomposed into a labor market composition effect (holding constant the initial within-group occupational structure), changes in the occupational structure within each worker group (holding constant the initial gender-education composition constant), and an interaction term. More precisely:

$$\pi_{18} - \pi_{01} = \Delta\pi = \sum_i s_{18}^i \pi_{18}^i - s_{01}^i \pi_{01}^i = \sum_i \Delta s^i \pi_{01}^i + \sum_i s_{01}^i \Delta\pi^i + \sum_i \Delta s^i \Delta\pi^i ,$$

Where, for each gender-education group i, π^i is the fractions of jobs in a given occupation group, s^i is the group's share of the total population, and the subscripts 01 and 18 indicate the years 2001 and 2018, respectively. The first term captures the "composition effect" owing to the change in the population share of demographic groups over time. The second term is the "propensity effect" due to changes in the fraction of individuals within groups. The third represents the co-movement between the two.

Table 2 reports the results of the shift-share decomposition. The table corroborates the finding that non-college educated workers are the only group experiencing large job polarization, while at the aggregate level this phenomenon is mostly accounted for by changes in labor force composition. The propensity of abstract jobs for college groups has declined, even as the proportion of workers with a college degree has steadily increased.[10] This suggests that new college graduates face a declining probability of obtaining abstract jobs.

C. Life-cycle Profiles and Cohort Differences

Is the decline of routine jobs homogeneous across young and old workers? This question is important for understanding the long-run implications of structural change as older workers retire and new cohorts enter the labor force. Further, since occupations are closely associated with wages, inter-cohort differences have significant implications for earnings inequality. In this section, we introduce cohorts as an additional dimension of analysis.

Figures 4 and 5 present synthetic cohort plots of the employment share in each occupation for females and males, respectively, with and without a college degree. For the period 2001-2018, we divide the labor force into 5-year cohorts based on birth year. For each cohort, we plot the value of the variable of interest and the average age during a given wave of the LFS (we take averages

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[9] Figure AI.1 in Annex I shows that these trends were already present in the second half of the 1990's. Before 2001, the LFS uses the SOC1990 classification, which introduces large breaks in the series.

[10] The "propensity" terms for abstract jobs of male and female college workers sum up to -1.16, more than 15 percent of the 7.62 increase in the share of abstract jobs.

across 2-year windows to reduce noise). Given the time range of the data, the earliest cohort is comprised of workers born between 1940 and 1944 (i.e., Cohort 1940), while the last cohort includes those born between 1990 and 1994 (i.e., Cohort 1990).

Each line in **Figures 4 and 5** pertains to a different cohort. The variation over age for a given cohort is informative of the overall life-cycle profile of a variable. At the same time, changes over cohorts for a given age shed light on aggregate changes in the economy over time, which could affect all cohorts equally or only a subset. These plots reveal several patterns:

- Overall, the life-cycle profile is upward sloped for abstract jobs but is downward sloped for routine and manual jobs. The figures suggest that workers progress into higher-skill occupations over the course of their careers. The importance of occupational mobility for wage growth is not new to the literature.[11] However, the figures highlight the stark differences in the magnitude of this channel across worker groups. College-educated workers exhibit the largest progression into abstract jobs: the gap between the lowest and highest points on the cohort plot is almost 50 percentage points. The same metric for non-college workers is less than 20 percentage points.

- Non-college workers exhibit marked differences across cohorts, particularly for females. The left panels of **Figure 4 and 5** show that there are significant differences across cohorts in the likelihood of being in manual and abstract jobs for females. While the share of females in abstract occupations has risen over time for workers aged above 40, it has remained unchanged for earlier ages. On the other hand, young workers in later cohorts are more likely to be employed in manual jobs compared to earlier cohorts. One interpretation of this finding is that the reallocation away from routine jobs has induced a process of skill upgrading for older generations of non-college females but occupational downgrading for younger females just entering the workforce.

- Both male and female college-educated workers have experienced a fall in the share of abstract occupations across successive cohorts. This is mirrored by a higher share in manual and routine jobs. This pattern suggests that a higher share of college-educated workers is now employed in low-skill occupations compared to two decades ago, contributing to occupational downgrading at the aggregate level. The differences are quantitatively large: the fraction of workers born in the early 1970's in abstract jobs in 2018 is more than 5 percentage points lower than that of workers born in the late 1950's when they were of the same age. This result contrasts with those of Cortes et al. (2018) for the US, who find that only high-skill males have experienced a fall in abstract employment while females are more likely to be in abstract jobs.

[11] See for instance Kambourov and Manovskii (2009), and Groes et al. (2015).

III. Estimating Age, Cohort, and Year Effects

A. Employment Propensities

In this section, we apply a linear probability model to quantify the above observations by disentangling age, year, and cohort effects. Because of collinearity issues in identifying all three sets of effects, we impose some parametric assumptions. First, the cohorts are comprised of 5-year intervals, so that they are not perfectly collinear with the age and year variables. Second, we model age through a cubic polynomial rather than a set of dummy variables.[12] For each occupation, the dependent variable equals one if individual *i* at time *t* is employed in a given occupation and zero otherwise. The regression is run separately for each gender-education worker group.[13] The baseline specification for a worker *i*, from cohort *c*, at time *t* is

$$\textit{Employed in } X_{\text{it}} = \alpha_0 + \alpha_1 age + \alpha_2\, age^2 + \alpha_3 age^3 + \gamma_t + \delta_c + \epsilon_{it} \qquad (1)$$

where *X* is routine, abstract, or manual occupation, γ_t is the year effect, and δ_c is the cohort effect.[14] The age polynomials capture the employment share in each occupation over a worker's age that is common to all cohorts and constant over time. The year and cohort effects represent upward or downward shifts in the age profiles that are common to all workers in a given year or for workers belonging to the same cohort, respectively, relative to the reference cohort (1940) and the reference year (2001). In other words, year effects trace the aggregate shifts owing to changes in the economy over time rather than the generational turnover of workers. Cohort effects capture aggregate shifts in occupational composition driven by inherent "unobserved" differences between successive generations of workers. The equation is estimated through Ordinary Least Squares (OLS) using robust standard errors.

It is important to note that specification (1) does not incorporate heterogeneity in the effect of time variation across age (i.e., the year effects γ_t are not interacted with the age variable). As a result, this specification does not capture the potentially heterogeneous impact of business cycle fluctuations on workers of different ages, and only captures the average change over time in the employment propensity of each occupation.[15] This choice is motivated by our interest in understanding job polarization as a medium-to-long-run phenomenon. This restriction is also applied to the wage equation in the next subsection.

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[12] The results are robust to replacing the set of year effects dummies with a linear time trend (available upon request).

[13] We exclude the unemployed and those out of the labor force. The sample sizes for each group are: non-college females: 882,428, college females: 555,562, non-college males: 1,001,764, college males: 529,415.

[14] We also included in the specification a set of dummies for quarter of the year).

[15] In this set-up, identifying true cohort effects requires observing each cohort through a long enough period for the effect of a specific recession or recovery to wane.

The left side panels of **Figure 6** report the predicted age profiles of employment in each occupation that is common across all cohorts. These paths are computed separately for each worker group through the estimated coefficients of the age polynomials. The profiles reflect the overall hump-shaped path of the cohort plots, outlining the average life-cycle trajectory of each occupation and how it varies for different groups of workers. For instance, high-skill workers feature a steeper progression into abstract jobs compared to low-skill occupations.

In **Figure 7**, the left side panels report the year effects of employment propensity in each occupation type by worker group, together with the 95 percent confidence intervals. The sets of year dummies trace almost-linear upward or downward paths reflecting the average change of each occupation within a worker group.[16] These shifts are significant in magnitude: for each worker group, with the exception of non-college males, there is at least one occupation where the magnitude of the 2018 coefficient is 3 percentage points or larger. Once again, the most substantial period effect is the decline in routine jobs for non-college females (around 10 percentage points by 2018), followed by the fall in abstract jobs for college males. Qualitatively, it is worthy of note how the trends in employment composition are inverted for low- and high-skill workers, with abstract jobs rising for the former and falling for the latter.

The cohort dummies plotted in the left-hand side panels of **Figure 8** provide several insights regarding inter-generational differences. These can be interpreted as the degree of heterogeneity across generations around the aggregate trends represented by the year effects. For non-college females, they trace hump-shaped paths, implying that the largest differences in occupational composition occur between the youngest cohorts and those born in the 1960's (i.e., the middle of the sample). For instance, while the Baby Boomer cohorts were progressively less likely to enter a manual job compared to previous cohorts, the trend reversed when the "Generation X" (born between 1965 to 1979) entered the labor force. The youngest Millennial females (born 1990-1994) without a college degree are almost 10 percentage points more likely to be in a manual occupation compared to similar workers born in the mid-1960's. Combined with the year effects, this reversal implies that, while on the whole manual jobs have fallen for low-skill females (year effects), this was not the case for younger generations

Non-college males also show quantitatively large cohort effects, with almost linear paths. The cohort effects for routine jobs suggest that non-college males born in the early 1990's are about 8 percentage points less likely to be in a routine occupation compared to the post-WWII cohorts. Younger generations are more likely to enter *both* manual and abstract jobs. Hence, for recent cohorts of low-skills men, the job polarization taking place at the aggregate level (year effects) is enhanced by cohort turnover.

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[16] It is worth noting that the aggregate shifts represented by the 2018 coefficients intuitively offset each other across occupations within a worker group.

Interestingly, the cohort effects are of more modest magnitudes for college-educated workers, implying low inter-generational differences in job propensities. The only pattern of substantial size is the fall in manual jobs for females.

Overall, the age-year-cohort decompositions paint a complex picture of structural change, adding an additional dimension of inequality to job polarization. Finally, college-educated workers exhibit time trends applicable to all generations that partially counteract job polarization at the national level, with abstract jobs exhibiting a secular decline.

B. Wages

Since a subset of the LFS workers report their labor earnings, we use the same specification as in (1) to decompose (log) wages W_{it} into age, year, and cohort effects:

$$\text{Log}(W_{ict}) = \alpha_0 + \alpha_1 age + \alpha_2\, age^2 + \alpha_3 age^3 + \gamma_t + \delta_c + \epsilon_{it} \quad (2)$$

The age polynomials, shown in the right side panels of **Figure 6**, reveal a generally increasing hump-shaped path. However, there are significant differences across specific demographic groups and occupations both in the average wage level and its progression as workers age. The year effects, in the right panels of **Figure 7**, show a common business cycle movement for all samples, with positive wage growth until 2007, a steep decline during the Great Recession, and a protracted stagnation thereafter. However, the magnitude of the fluctuations differs across specific groups. In particular, wages of high-skilled workers have stagnated in the last decade.

College-educated workers exhibit rising cohort effects (right panels of **Figure 8**), implying that younger generations are likely to earn higher wages compared to older ones throughout their life-cycle. Although standard errors are larger compared to the employment regressions, many coefficients are statistically significant at the 95% level.[17] In most cases, wages for the youngest college workers are on average 10 to 20 percent higher than those of workers born after WWII (without accounting for aggregate growth in wages that took place over the last 70 years).

On the other hand, non-college workers born since the late 1970's have witnessed a fall in the permanent component of their real wages across all occupation groups. This decline is especially pronounced for females. For instance, females born in 1990-1994, on average receive wages that are 14 percent lower than those of female workers born in 1965-1969 within all types of occupations.

[17] The confidence intervals for cohort effects tend to increase for younger cohorts. This is due to the choice of Cohort 1940 as the reference group. This cohort has a relatively smaller sample size, as it was only followed for a few years after 2001. The relative wages of other cohorts, especially when also small in sample size, are therefore noisily estimated compared to the reference group. Any other cohort could be chosen. In particular, choosing a cohort in the mid-1960s, which is present through the whole period and hence has a larger sample size, would lower the standard errors.

C. Sensitivity Analysis

To check the robustness of our results, we estimate the linear regressions in (1) and (2) using alternative samples. In particular, we (i) include immigrants (more precisely, foreign-born workers), (ii) we exclude the self-employed, and (iii) extend the sample backwards until 1984 by using cross-walks between different occupational classifications. The key results hold in all cases with only minor quantitative changes and are available upon request.

IV. Counterfactuals Exercises: Looking Back and Looking Ahead

The age-year-cohort regressions uncover significant heterogeneity across the workforce. However, all regression coefficients should be considered jointly in order to fully interpret outcomes through the lens of inter-generational inequality. For example, wages in manual occupations for non-college females have risen in the past 20 years in the aggregate, as shown by the year effects in **Figure 7**. However, the declining cohort effects suggest that wage growth has been subdued for the youngest generations. Combined with recent employment trends, which show a rise in the share of manual jobs among young females, this suggests that young low-skill workers are increasingly likely to enter low-paying jobs and to remain there over their careers. In this section, we provide a comprehensive framework to understand the impact of each factor for aggregate wage dynamics over time.

We carry out a set of counterfactual exercises to gauge the quantitative relevance of cohort and year effects and labor force composition changes for inter-age earnings inequality. We first examine the drivers of wage growth over the period 2001-2018. Using the same tools, we then take a forward-looking approach to project each cohort's average lifetime earnings.

A. Decomposing Wage Growth Between 2001 and 2018

Based on the above definitions of occupation types and worker groups, the (predicted) average wage in the economy in year *t* can be computed as follows:[18]

$$W_t = \sum_i \sum_k s_t^{ik} \sum_o \widehat{p_t^{iko}} \ \widehat{w_t^{iko}}\,, \tag{3}$$

where i is the index for cohorts, k is the index for the demographic group, and o is the index for occupation type. The cohort-i group-k population share s_t^{ik} is taken from the LFS as the average share among employed workers across the four quarters of the year, using population weights.[19] The share of workers in each occupation $\widehat{p_t^{iko}}$, which can be regarded as occupational propensity, is computed using the estimated OLS coefficients from (1) and the average age of workers from

[18] Without loss of generality, the formula considers a year as one period and therefore does not account for quarters dummies, averaging out quarter effects over the year.

[19] More precisely, using shares of the total employed labor force.

cohort i in year t, age_t^i, together with the appropriate cohort and year dummies.[20] The wage $\widehat{w_t^{iko}}$ is computed in the same fashion from (2). For clarity of comparison with the counterfactual, it is useful to explicitly express them as functions of age, cohort, and year effects:

$$\widehat{p_t^{iko}} = p^k\left(age_t^i, cohort^i, year_t\right),$$

$$\widehat{w_t^{iko}} = w^k(age_t^i, cohort^i, year_t).$$

Figure 9 plots the predicted wage computed in (3) for each age group (21-34, 35-49, and 50-64) separately against the LFS series at annual frequency. While the fit is generally good, the main deviations from the empirical series occur during the years following the Great Recession. For the period 2008-2017, the wage of the young is overpredicted and that of older workers is underpredicted. This implies that the cyclical component of wages is larger for younger workers and has resulted in a more severe wage downturn after 2008. That is not captured by the regressions in (1) and (2), where the year effects are not interacted with age. This also suggests that our estimation does not confound differences in cyclical behavior (which drive transitory fluctuations in wage inequality) with cohort effects (which are permanent).

The first row of **Table 3** shows that the regressions, together with the change in composition, explain 55 percent and 97 percent of the increase in the wage gap between young and prime-age and old workers, respectively.[21]

There are several drivers of variation in W_t over time and across age groups. To examine their contribution, we construct counterfactual series for W_t. First, the composition of the population, represented by the vector of s_t^{ik}'s, changes as new cohorts enter the labor force (e.g., there are more female and college-educated workers in younger cohorts).[22,23] Second, cohort effects capture permanent differences across generations of workers in the propensity to be in each occupation and the average wage therein *conditional* on belonging to a given gender-education group. Finally, year effects encompass both cyclical fluctuations and long-term trends specific to the worker group-occupation type. Based on these considerations, the counterfactual series are as follows:

[20] Since the regressions are done on the log of wages, to obtain the level we take the exponent of the regression fitted value and then, assuming log-normal error terms, we multiply by exp($\widehat{\sigma_\epsilon}^2/2$), where $\widehat{\sigma_\epsilon}$ is the Root MSE of the regression.

[21] This suggests that the unexplained fractions of the increases are attributable to the business cycle effects.

[22] There is also variation over time within the same cohort, as different groups of workers are affected differently by the business cycle or have varying degrees of attachment to the labor force.

[23] Entrance and exit of cohorts into the labor force, due to the imposed age interval 21-65, is represented by shares equal to 0. For instance, as Cohort 1990 workers were on average 9 years old in 2001, $s_{2001}^{11\,k} = 0$.

a. Only year effects

$$W_t^{YEAR} = \sum_i \sum_k s_{2001}^{ik} \sum_o p^k\left(age_{2001}^i, cohort^i, year_t\right)\ w^k(age_{2001}^i, cohort^i, year_t)$$

b. Only cohort effects

$$W_t^{COHORT} = \sum_i \sum_k s_{2001}^{ik} \sum_o p^k\left(age_{2001}^i, \widetilde{cohort}_t^{\iota}, 2001\ \right)\ w^k(age_{2001}^i, \widetilde{cohort}_t^{\iota}, 2001)$$

where $\widetilde{cohort}_t^{\iota}$ is a counterfactual cohort dummy constructed to allow for empirically-consistent cohort turnover while all other components, including the population shares, remain fixed to their 2001 levels.

c. Labor force composition

$$W_t^{COMP.} = \sum_i \sum_k s_t^{ik} \sum_o p^k\left(age_t^i, \widetilde{cohort^{\iota}}_t, 2001\ \right)\ w^k(age_t^i, \widetilde{cohort}_t^{\iota}, 2001)$$

where $\widetilde{cohort}_t^{\iota}$ is a counterfactual cohort dummy constructed to maintain the cohort distribution constant to the 2001 distribution.[24]

Figure 10 plots the actual wage and the counterfactuals listed above. Several patterns emerge. First, the contribution of the year effects (purple triangles), which capture cyclical fluctuation in wages, is similar across age groups.[25] However, the results do not show an upward trend, suggesting that aggregate wage growth over the period under study must be explained by either shifts in labor force composition or generational turnover.

Compositional changes (red diamonds) account for growth in wages for all age groups. The total contribution to wage growth is similar for young and prime-age workers (about 1.5 GBP over the period) but is half the magnitude for older workers. These results have intuitive explanations. The share of college-educated workers has risen steadily among younger generations. Since high-skill workers receive higher wages within each occupation and are more likely to be employed in abstract jobs, the compositional shift to a highly skilled labor force has underpinned wage growth for the younger cohorts relative to older ones. Interestingly, the composition-only wage

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[24] As an illustrative example, in 2001 the mean age of Cohort 1965 is 34. Under the alternative dummies, when in 2006 Cohort 1970 is on average 34 years old, $\widetilde{cohort}_{2006}^{1970} = cohort^{1965}$, and in the years between 2001 and 2006, $\widetilde{cohort_t}^{1970}$ is a weighted average of $cohort^{1965}$ and $cohort^{1970}$ based on the distance between the average age of cohort 1970 in that year and 34.

[25] This result is only partly explained *a priori* by the specification of the regression discussed in the previous section. There can still be differences accounted for by year effects coming from the relative exposure of different groups of workers to occupations with falling or rising wages.

counterfactual overshoots the actual wage for young workers. Finally, the cohort effects (green squares) drive diverging trends across the three groups, with the young experiencing a fall in average wages, wages of the prime-age workers remaining unchanged, and old workers experiencing rising wages. These diverging paths indicate that factors other than demographic composition are driving inter-generational wage inequality.

Table 3 quantifies the contribution of each factor to the change in the wage gap between 2001 and 2018. As noted above, the gap in hourly wage for the young relative to prime-age workers increased by GBP 1.26. Our regression accounts for over half this increase, driven largely by cohort effects. Year effects and compositional changes account for only a small fraction of the rise. Similarly, the gap in hourly wages for young versus old workers rose by GBP 0.82 during this period. The regression accounts for 97 percent of this increase, but labor market composition changes partially offset the cohort effects.

The cohort-effects counterfactual captures the growing earnings inequality across ages that is not explained by labor force characteristics. The previous section showed that generational differences in occupational propensity and occupation-specific wages vary markedly by gender and education. **Figure 11** reports the same counterfactual exercise for each worker group. While wages have stagnated for all young workers, low-skill workers experienced a fall of around 10 percent over 2001-2018. Further, non-college females have experienced the lowest wage growth across all age groups, although the wage decline is most pronounced for young females.

It is worth noting that cohort effects in the OLS regressions are not restricted to sum to 0. As a result, the fact that the total contribution of cohort effects is negative for the young, almost nil for the prime-age, and positive for the old is not an artifact of the empirical analysis. Our findings suggest that the widening inter-age wage gap is not explained by either aggregate forces (i.e., year effects) or compositional changes but by other "unobserved" differences pertinent for recent labor market entrants.

B. Counterfactuals and Life-Cycle Projections

The second set of counterfactual exercises compute each cohort's expected lifetime earnings and assess the contribution of year and cohort effects. While the previous exercise focused on understanding the drivers of wage growth over the past 18 years, the spirit of this section is forward-looking.

As an illustrative example, **Figure 12** plots the share of employment in abstract jobs for college-educated men in Cohorts 1960 and Cohort 1985 across a worker's age. The circles and diamonds report the best-fit values from the estimation of (1) for the two cohorts, while the dashed and solid lines plot the projected path pre-2001 and post-2018. All else equal, the dashed blue line shows that when Cohort 1985, on average, is 56 years old (in 2040), their projected share of abstract jobs will be almost 5 percentage point higher than that of Cohort 1960 at the same age in 2018. The dotted blue line and the dash-dot red line decompose this difference into a permanent cohort effect (i.e., Cohort 1985 has a higher propensity for abstract jobs compared to

Cohort 1960) and year effects (which affect both cohorts negatively between 2001 and 2018 but at different stages of their lives).[26] Extending this exercise to all occupation types and the average wages therein, we can project earnings prospects for each cohort throughout their entire working life.

Based assumptions regarding occupational shifts and wage growth pre-2001 and post-2018, the lifetime wage of workers in a group k and cohort i can be computed as follows:

$$W^{ik} = \sum_{t=t_0^i}^{T^i} \beta^t \sum_o \widehat{p_t^{ik}} \ \widehat{w_t^{ik}} \tag{4}$$

where $\widehat{p_t^{ik}}$ and $\widehat{w_t^{ik}}$ are as defined as in the previous section, 0<β<1 is a discount rate, and the index t encompasses the working years of the cohort from t_0^i to T^i. In computing $\widehat{p_t^{ik}}$ and $\widehat{w_t^{ik}}$, we apply the 2001-year effects for all preceding years and the 2018 effect for all subsequent years, thus assuming it to be a permanent change. For each cohort and worker group, we compute W^{ik} and two counterfactuals in which cohort and year effects are excluded, respectively. For the cohort exercise, we set all cohort effects equal to Cohort 1940. For the year counterfactual, we set all year fixed effects equal to their 2001 value. We assume that each year is discounted at the rate of 2.5 percent (i.e., β=0.975).

Figure 13 presents the results. For a given cohort *k,* a positive blue bar indicates that the cohort effects (relative to Cohort 1940) contribute positively to lifetime earnings. Similarly, a positive orange bar indicates that the entire set of year effects from 2001 to 2018 contribute positively to lifetime earnings. The figure shows that cohort effects have contributed positively to workers' lifetime earnings over successive generations. That is, conditional on belonging to a given worker group, younger cohorts have higher earnings prospects over the course of their entire careers. However, there are large differences across workers. Lifetime earnings are higher for recent cohorts of college females. Non-college females, on the other hand, have the lowest positive contribution of cohort effects for Cohorts 1945 to 1980, with the effect turning negative and large for workers born since 1985.

Year effects also indicate diverging impacts for high- and low-skill workers, contributing negatively to the lifetime earnings of the former and positively to the latter. The negative effect for high-skill workers owes to occupational downgrading and wage stagnation discussed above. Although these developments affect all cohorts, the impact on lifetime earnings is larger for the youngest cohorts because this persists over a larger fraction of their life-cycle. As older generations only experience these negative shocks towards the end of their career, the total effect on lifetime earnings is modest. A similar intuition applies to the larger positive contribution of year effects for low-skill workers. Of course, assumptions about wage growth in future years

[26] We also document this comparison in shares and wages for all worker groups and occupations (results available upon request). Overall, our findings suggest that large degree of heterogeneity in cohort and year effects across groups can have a significant impact on workers' life cycles.

are also crucial for this result. Alternative scenarios that assume positive wage growth after 2018 would mitigate the total contribution of year effects for younger cohorts.

As cohort and year effects enter into both $\widehat{p_t^{ik}}$ and $\widehat{w_t^{ik}}$, we can also disentangle the employment propensity and wage channels by computing counterfactual lifetime earnings that exclude only cohort (year) effects in either occupational shares or wages**. Figure 14.a** shows that the cohort contribution on earnings is mostly driven by the effect on wages within each occupation type rather than the propensity of being employed in different occupations. However, for non-college females the magnitude of the propensity channel is non-trivial and around one third of the total cohort effect. **Figure 14.b** reports the same exercise for the year effects. Once again, the effects on wages is found to be the main driver. However, aggregate changes in occupational propensities account for a third to a half of the total year effects for all high-skill workers.

V. What Lies Behind Cohort Differences?

Cohort effects reflect all changes in wages and employment propensities that are not accounted for by age, common time trends, or any other explanatory variable included in the regression model. These changes could be connected to recent trends that disproportionately affect recent labor force entrants. Moreover, while we showed that these trends precede the Great Recession, recent studies show that cyclical fluctuations and structural transformation are closely intertwined. The nature of short-term dynamics could thus depend on slow-moving macroeconomic fundamentals.[27]

In this section, we consider possible factors contributing to the relatively larger slowdown in wage growth for the youngest cohorts. To jointly explain the "productivity puzzle" and our findings, the forces driving the aggregate wage slump would have to act through a channel that is pertinent for younger workers (e.g., labor market entry) or has a heterogeneous effect across age groups. The discussion below is organized into three partly-overlapping topics: skills, underemployment, and industrial composition.

A. Skills Formation and Mismatch

Skill mismatch could be a potential driver of inter-age wage inequality. Abel et al. (2016) show that returns to both secondary and higher-education degrees in the UK (measured through a Mincerian regression) have fallen steadily over the past 20 years. This finding suggests that the educational system may not be equipping workers with the requisite skills. UKCES (2014) documents a large-scale skill mismatch in the labor market: employers in low-skill sectors report a high incidence of skill deficiency, high-skill vacancies being hard to fill, and up to 4.3 million workers possessing skills above those required for their jobs. Patterson et al. (2016) show that

[27] See for instance Jaimovic and Siu (2012) for an argument based on long-run technological change.

mismatch between the occupations sought by unemployed workers and the jobs posted by firms contributed to a large decline in average worker productivity between 2007 and 2012.[28]

The lack of specialized technical and vocational degrees in the UK or the quality of higher education could be contributing to the skill mismatch.[29] Espinoza and Speckesser (2019), however, find that the returns to higher-level vocational degrees wane when workers reach their mid-20s (STEM subjects are somewhat of an exception). Belfield et al. (2018) also find a very mixed picture with respect to university degrees. They show that the wage premium from an undergraduate degree ten years after completion varies greatly depending on a student's gender and pre-university academic performance, the subject of study, and the quality of the institution attended.

Our results corroborate these findings, suggesting that the overall post-secondary education system (university and technical/vocational) may not be adequately meeting the new demands of the labor market. This is not just the case for new entrants but also for more experienced workers. Understanding whether the problem originates from the technical and vocational system or from the university system, or both, is beyond the scope of this work. As a preliminary pass, in Annex 3 we expand the analysis in Section III by separating the "college" groups into those with at least a bachelor's degree and those with some "further education". **Figure A3.1**. shows that occupational downgrading has characterized both groups of workers over the past two decades. Although the fall in the abstract share of jobs is substantially larger for the below-Bachelor's category, the increase in university attendance in recent decades (**Figure A3.2**) makes the deteriorating employment prospects of high-skill workers an important challenge.[30]

B. The Rise of Involuntary Part-Time Employment

Part-time and flexible employment arrangements favor labor force participation for workers with higher opportunity costs of working and those transitioning from study to employment. However, part-time work can result in underemployment if it reflects low labor demand. This lowers current income and prevents human capital formation, negatively affecting earnings throughout the career.[31] Bell and Blanchflower (2018a) show that underemployment rose sharply in many advanced economies in the aftermath of the Great Recession. Understanding the reasons for part-time work and its impact on wages is beyond the scope of our analysis and is

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[28] However, using alternative data for vacancies by occupation, Turrell et al. (2018) conclude that the regional mismatch between seekers and vacancies accounts for most of the aggregate mismatch.

[29] For instance, Mason and Rincon-Aznar. (2015) note that Germany and France possess higher shares of workers with specialized technical and vocational degrees than in the UK.

[30] The estimation of (1) and (2) for these two groups separately is available upon request.

[31] Besides the fewer hours worked, evidence shows that there exists a wage penalty from part-time work which is not explained by observable worker characteristics (Aaronson and French, 2005). Fernández-Kranz and Rodríguez-Planas (2011) also show that the penalty is persistent across the years. See also Bell and Blanchflower (2018b) for analysis specific to the UK.

the subject of a large literature. Nevertheless, we provide some evidence on part-time work and underemployment in the UK, particularly for young workers, in the last decade.

Figure 15 plots the share of workers in involuntary part-time employment by age group. This share increased by 3-5 percentage points, on average, for all workers under 35 years of age since 2008. For prime-age males, the share has remained almost unchanged. As a result, while in the early 2000's the rate of underemployment was comparable for all workers within a given demographic group, the rate for young workers began diverging around the Great Recession. In the case of males, the gap has not yet closed. In terms of cohorts, workers who entered the labor force since 2008 have not only faced a deep recession but also a labor market that was particularly unfavorable to them.

This finding is consistent with other evidence which suggests that the reduction in hours worked (the intensive margin) is procyclical and heterogenous across workers. Using employer-employee panel data for the UK, Schaefer and Singleton (2017) show that firms were able to respond to the Great Recession by recruiting more part-time workers. Further, hours worked by new hires in "entry-level" jobs, which tend to be filled by younger workers, fell markedly.

The relative importance of this channel in driving the inter-age wage and occupational gaps, however, remains an open question. For instance, the gap in involuntary part-time employment between young and old workers rose most markedly among males but our findings suggest that it is young low-skill females who have experienced the largest drop in earnings. Future research should shed light on the mechanisms through which underemployment leads to lower lifetime earnings and whether this is connected to the likelihood of transitioning from routine or manual to abstract jobs. Moreover, this channel appears closely aligned to the Great Recession and thus may not reflect the longer-term forces that underpin growing inequality since the early 2000s.

In the last decade, so called zero-hours contracts have r increased labor market flexibility for both employers and employees. However, they have been criticized for increasing income uncertainty on the employees' side given that working hours are not guaranteed. Although we focused the analysis on part-time work to leverage the greater data availability, an analysis of zero-hours contracts would provide a similar picture.[32]

C. Shifting Industrial Composition

Technological change and globalization in recent decades have also resulted in a changing industrial composition in many advanced economies. In this section, we investigate how job

[32] For instance, data available on the Office of National Statistics website (ONS, 2019, Dataset EMP17) shows that although only 2.7% of the employed workforce in 2019 is on zero-hours contracts, two thirds of them work part-time. Furthermore, a much higher percentage of zero-hours workers desire additional hours, an additional job, or a different job, thus suggesting a greater incidence of underemployment. Finally, workers below the age of 30 are more likely to be in zero-hours contracts.

polarization is aligned with the shifting industrial composition of the UK economy and the rise of the services sector.

As documented by previous studies, males and females tend to hold different jobs.[33] Moreover, there are clear differences in the specific occupations that account for job polarization dynamics by gender. **Tables 4** and **5** report the top 5 declining routine occupations in terms of share of employment between 2001 and 2018, and the top 5 growing abstract and manual jobs, by gender and for young and old workers, respectively. The two tables provide several insights:

- Within routine occupations, the bulk of the decline for males is in "manual-based" routine jobs (e.g. mechanics, postal workers) while for females it is in "cognitive-based" routine jobs (e.g. secretarial and clerical positions).
- The main abstract occupations that have experienced increases in employment share, include education, health, and managerial professions. The growth in employment share in the ICT sector is only evident for men.
- Manual jobs have increased in "caring and assistance" occupations (largely healthcare) and the "hospitality" services sector.
- Although the top growing and shrinking occupations are similar for young and older workers, the magnitudes of these changes tend to be substantially larger for the young. This corroborates the finding that structural transformation over the past two decades has, to a large degree, occurred through the entrance of new generations into the labor force.

Next, we jointly analyze shifts in industrial and occupational compositions. The previous results suggest that growing and shrinking occupations are concentrated in specific sectors, reflecting the decline of manufacturing and rise of the service economy. **Figure 16** reports the total change in the employment share of each industry between 2001 and 2018 for young workers by occupation groups.[34] A few trends stand out. First, rising employment share in growing sectors (education, healthcare, real estate sectors) is reflected in more abstract and manual jobs being created, while routine employment is falling largely in shrinking sectors (manufacturing, sales, transport). Second, for males, the fall in routine jobs is concentrated in the manufacturing and transport sectors, while for females it is more evenly spread among clerical jobs in different industries. Finally, as previously noted, the growth of manual jobs for low-skill females is in the healthcare and social services sector, restaurants and hotel services, and other community-based activities.

To what extent can this industrial shift account for the slowdown in wages? As noted by other studies, some of the highest-growing industries like education and healthcare are not

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[33] See for instance, Brussevich et. al (2018).

[34] For brevity, we focus on young workers, as this group has experienced the most sizable shifts.

traditionally associated with high wages (Abel et al., 2016; Thompson et al., 2016).[35] Moreover, recent employment growth in these sectors was not associated with higher-than-average productivity growth (Forth and Rincon Aznar, 2018), implying that the overall reallocation of workers across industries adversely affected aggregate wage growth.

While sectoral reallocation has undoubtedly underpinned transformation in the UK's labor market, it does not fully explain our findings. For instance, both young and older workers have transitioned into the same industries. However, as shown previously, the wage slowdown mostly affected the young. Furthermore, other studies show that, despite the reallocation towards low-productivity sectors, all industries were commonly affected by an aggregate slowdown in productivity (Dolphin and Hatfield, 2015).

VI. Conclusion and Policy Implications

This paper uses a life-cycle framework to examine the link between inter-age wage inequality and job polarization in the UK. The life-cycle lens allows us to understand the drivers of structural change and derive quantitative estimates of its impact on labor market prospects.

We document stylized facts that show that labor market prospects for all workers born since 1980 have deteriorated although through different channels. First, there has been a "hollowing out" of employment for all low-skill workers in the UK. Second, within each occupation, the wages of younger low-skill workers have fallen permanently. Finally, we find evidence of occupational downgrading for workers with a college education: a lower share of employment in abstract-task jobs and falling wages in recent decades. These cohort-level differences imply a large fall in cumulative expected lifetime earnings of the youngest low-skill workers of 7 to 15 percent relative to the generation of workers born in the 1960's. There are also substantial gender differences, with young low-skill females experiencing the largest fall in earnings.

Our analysis points to a number of areas where policy intervention may be needed to address the growing inter-generational earnings gap and its implications.

- **Education and Skills.** Declining employment share in abstract occupations and stagnating wages of high-skill workers call for an evaluation of the overall strategy to build a competitive labor force. For instance, Belfield et al. (2019) show that low wage premia arise from heterogeneous university quality, subjects of study, and previous educational attainment. This suggests the need for appropriate education and training policies to reduce skill mismatch.

- **Labor market entry.** Related to the point above, the large cohort effects in both occupational propensity and wages point to a worsening of labor market prospects for new entrants. This is also corroborated by the larger rise of involuntary part-time work for young

[35] Additionally, these industries have a higher concentration of part-time and zero-hours contracts (ONS Dataset EMP17).

workers. While part-time employment could ease transition into the labor market, earning prospects could fall if workers are not able to increase hours worked when needed. The problem of labor market entry is more critical for low-skilled workers, who have experienced the largest fall in earnings among the youngest cohorts.

- **Social insurance.** Young workers today not only earn less than previous generations at the same age (conditional on a given skill level), but this disadvantage could persist throughout their lives. Today's young workers face lower lifetime earnings and will reach retirement with a defined contribution pension system. Their income upon retirement will therefore be lower and spread over a longer period as average life expectancy increases. A crucial implication is that the social safety net targeted to the current elderly may require a rethink to sustain the needs of future generations.

- **Comprehensive analysis of welfare of young vs. old.** Our analysis has focused on inter-generational disparities in employment and earnings. However, a growing body of evidence shows that the young in the UK are faring worse than the old in many other respects, including wealth accumulation and housing. The geographic dimension of job polarization exacerbates this problem. For instance, both high-skill and low-skill jobs have become increasingly more concentrated around urban centers, where the cost of living is higher and the supply of housing more constrained. Hence, policies may need to focus on the broader generational divide in living standards and its socio-political repercussions.

This paper offers a new set of empirical facts to use as benchmark for theories of structural change. Our findings also point to the need for theory to explain the heterogenous impact of job polarization and inter-generational inequality. For instance, the sharp rise in university education, together with unobserved heterogeneity in productivity and skills, could explain the different development of cohort-level disparities for college or non-college educated workers through selection effects. Integrating endogenous labor supply would also provide a more nuanced perspective on lifetime earnings since young workers today face a higher retirement age and may further increase their hours of work to compensate for lower wages. On the empirical side, many lines of inquiries remain open. For instance, differences in patterns of job polarization and labor market outcomes of specific demographic groups in the UK and the US point to the need for better understanding the underlying drivers of structural transformation across countries. Finally, it is important to examine the interaction of these trends with policies implemented in the UK that particularly targeted specific groups of the labor force, such as the National Living Wage and the Working Families' Tax Credit. We leave these and other questions for future research.

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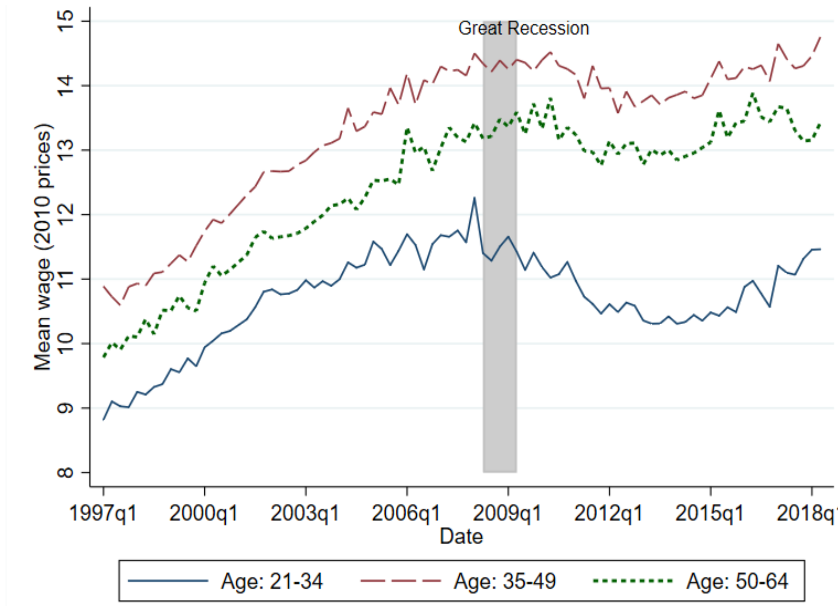
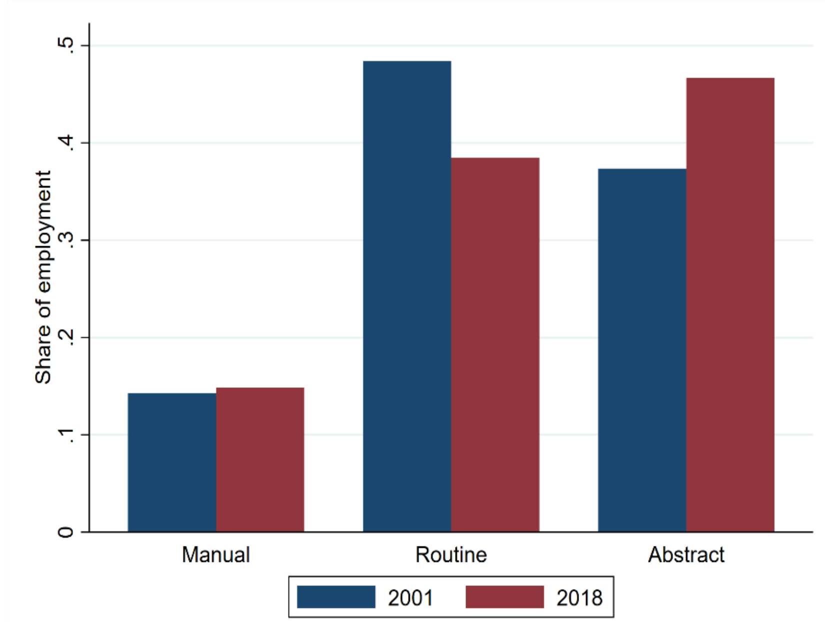
FIGURES

Figure 1. Mean Hourly Wage by Age Group in the UK, 1997-2018



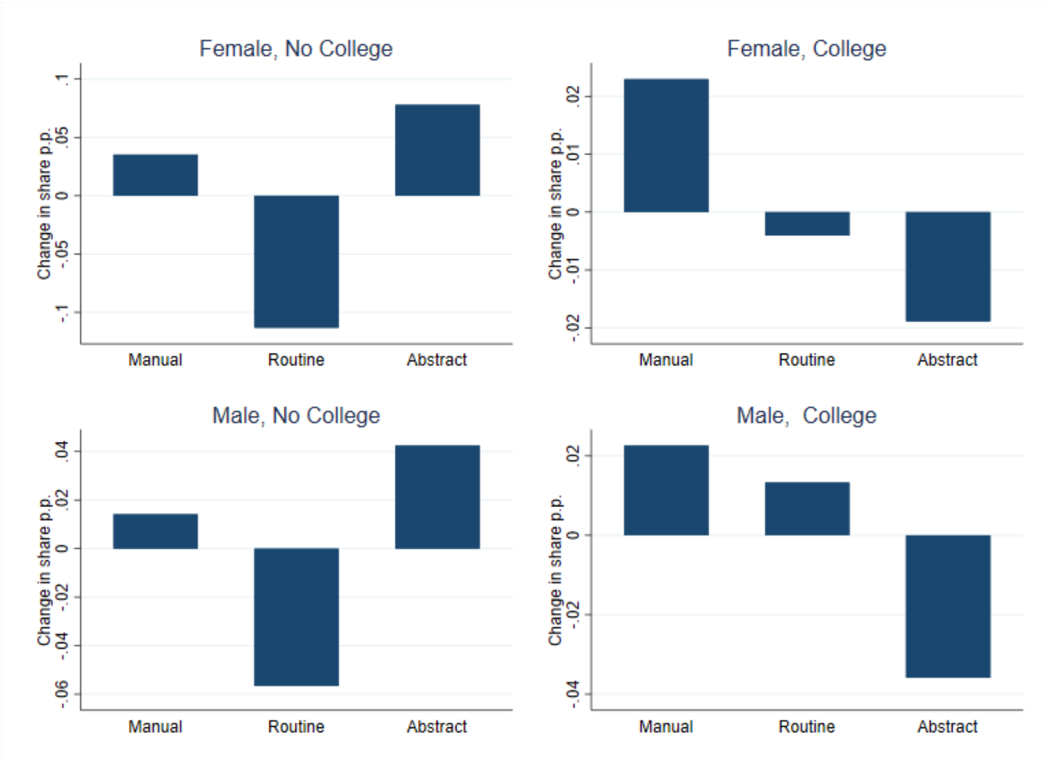
Source: LFS and authors' calculations. Wages are in GBP, chained at 2010 prices through the UK's Consumer Price Index. The grey shaded area represents the quarters of the Great Recession (2008q2-2009q2).

Figure 2. Employment Shares of Manual, Routine, and Abstract Occupations, 2001 and 2018



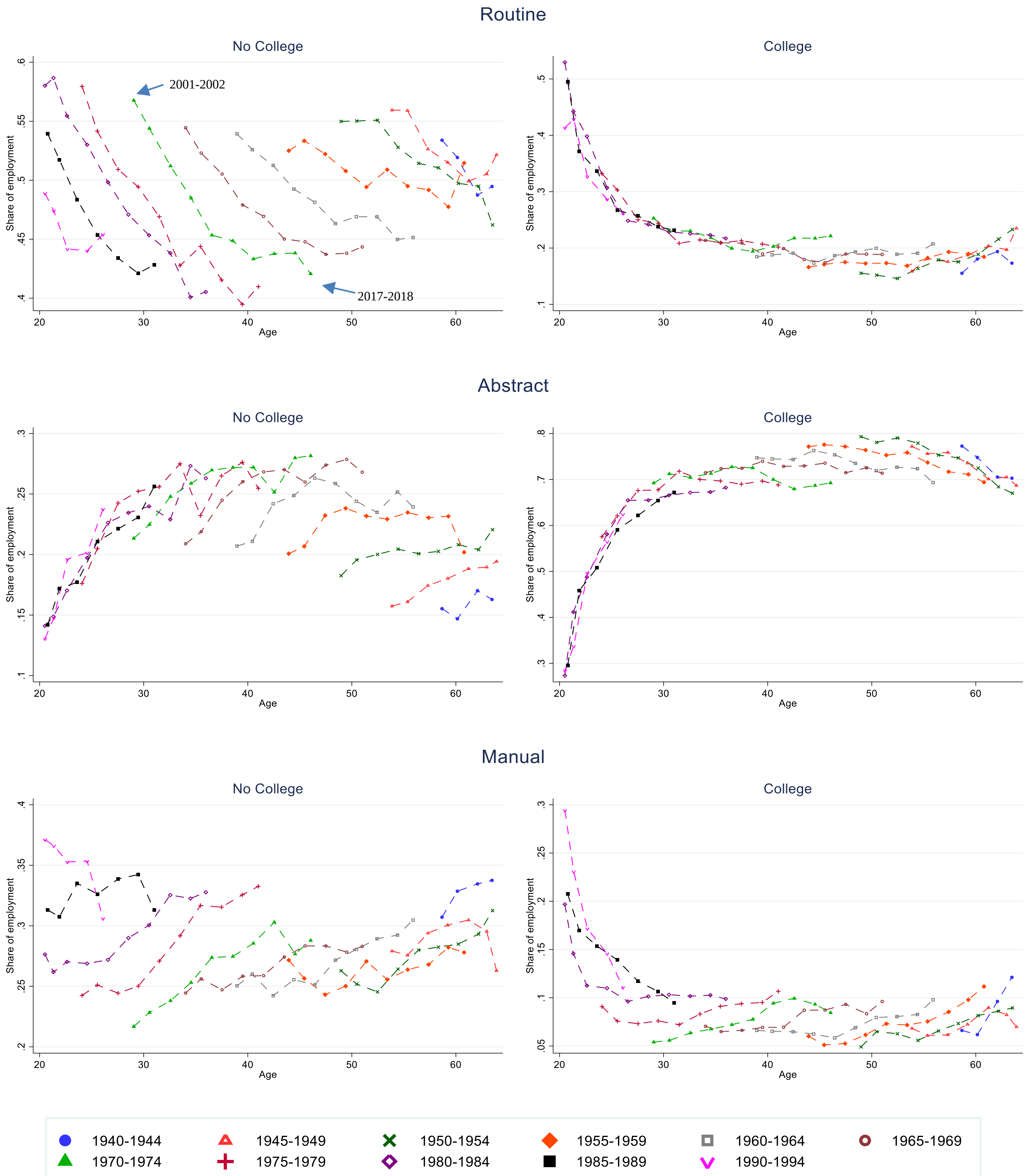
Source: LFS and authors' calculations. The blue and red bars report the share of employment in each occupation group in 2001 and 2018, respectively.

Figure 3. Change in Employment Shares of Manual, Routine, and Abstract Occupations by Worker Groups, 2001-2018



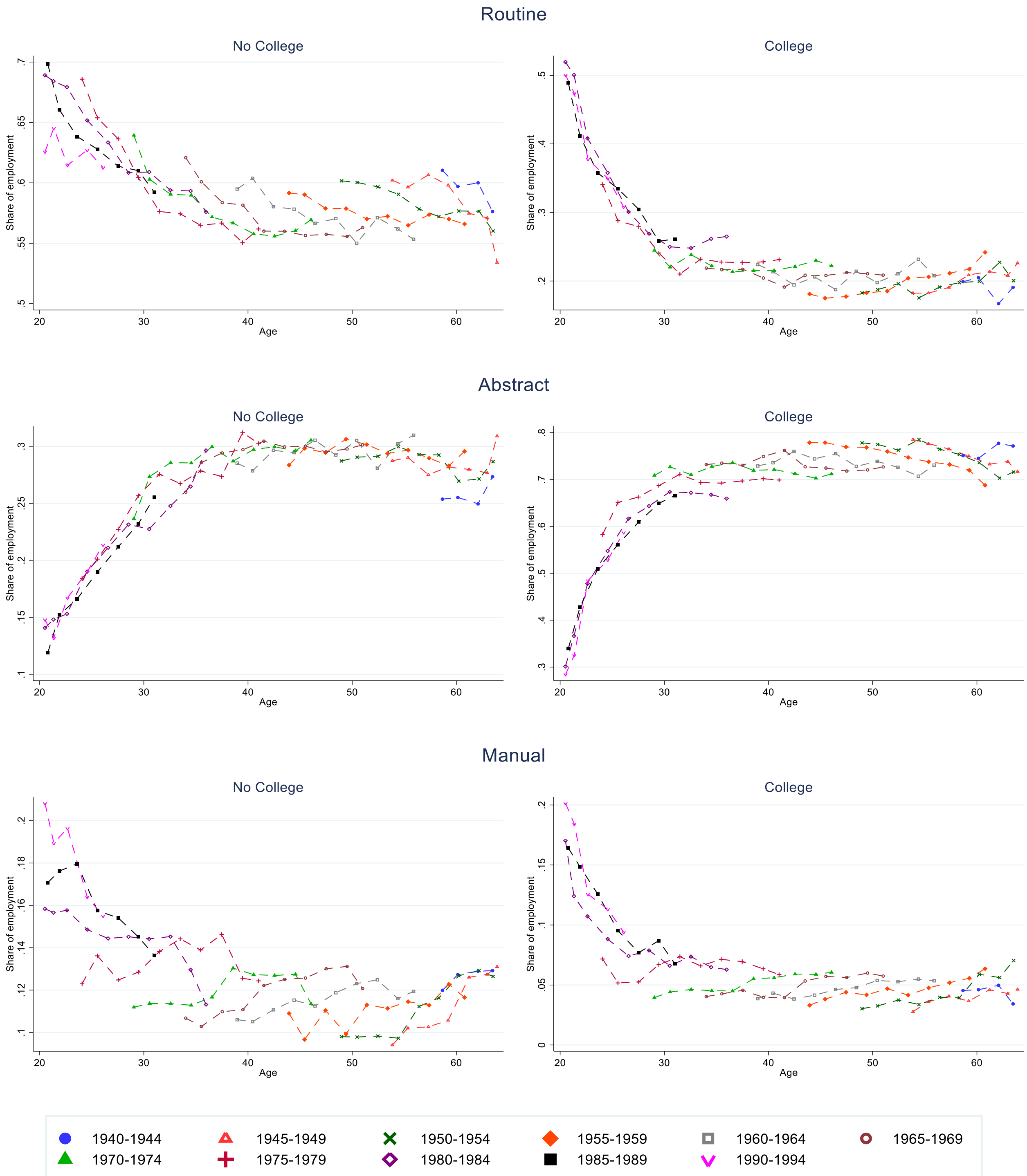
Source: LFS and authors' calculations. The blue bars report the change in the share of employment in each occupation group between 2001 and 2018 by gender and education group.

Figure 4. Cohort Plots for Females with and without a College Degree, 2001-2018



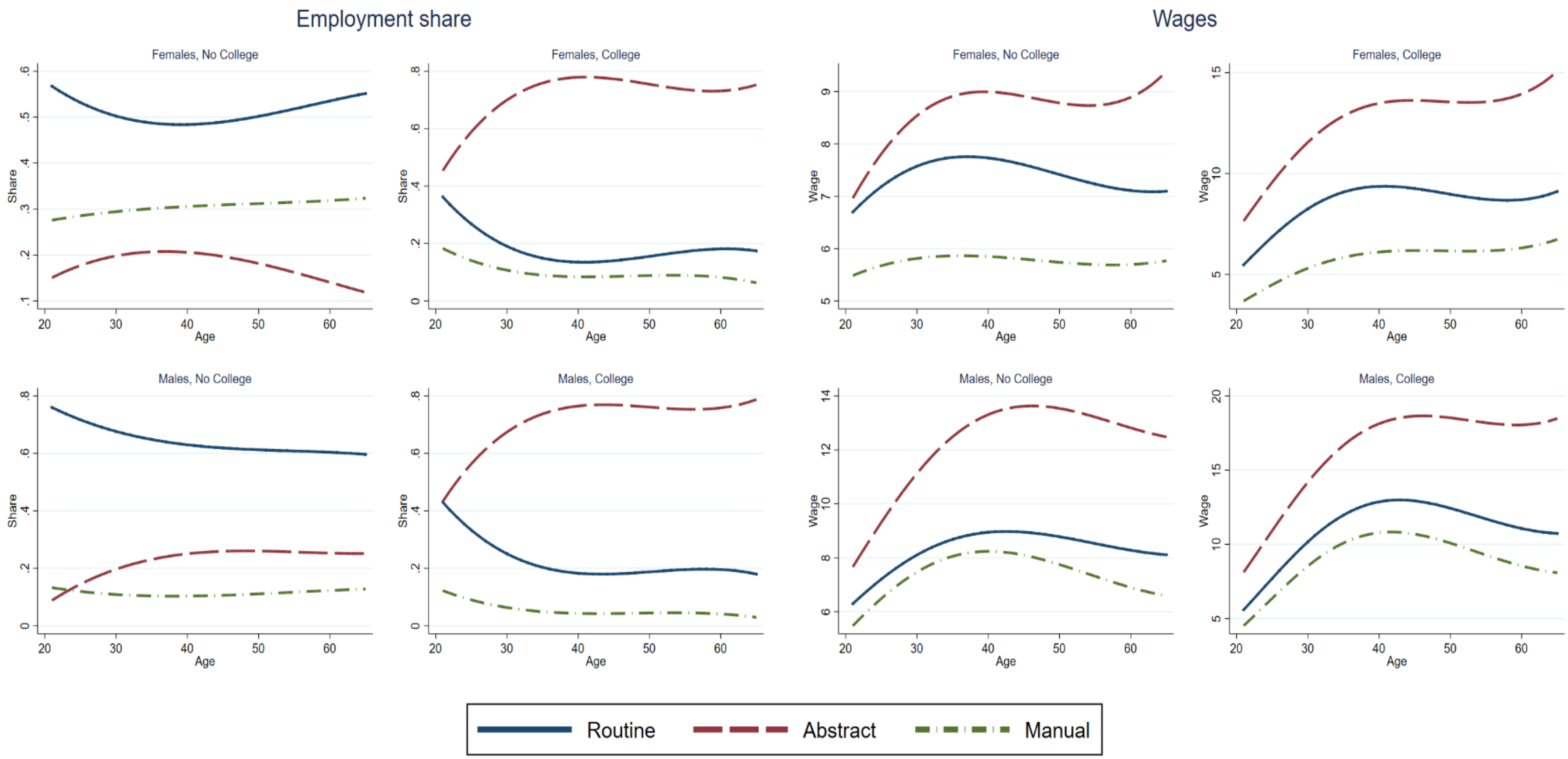
Source: LFS and authors' calculations.
Note: Each marker reports the share of employment in a given occupation, for a given cohort of females at a given age by education level. Markers report averages across two years of the LFS, from 2001-2002 until 2017-2018. Not all cohorts are present in all years as the plot is restricted to the age range 21-65.

Figure 5. Cohort Plots for Males with and without a College Degree, 2001-2018



Source: LFS and authors' calculations.
Note: Each marker reports the share of employment in a given occupation, for a given cohort of males at a given age by education level. Markers report averages across two years of the LFS, from 2001-2002 until 2017-2018. Not all cohorts are present in all years as the plot is restricted to the age range 21-65.

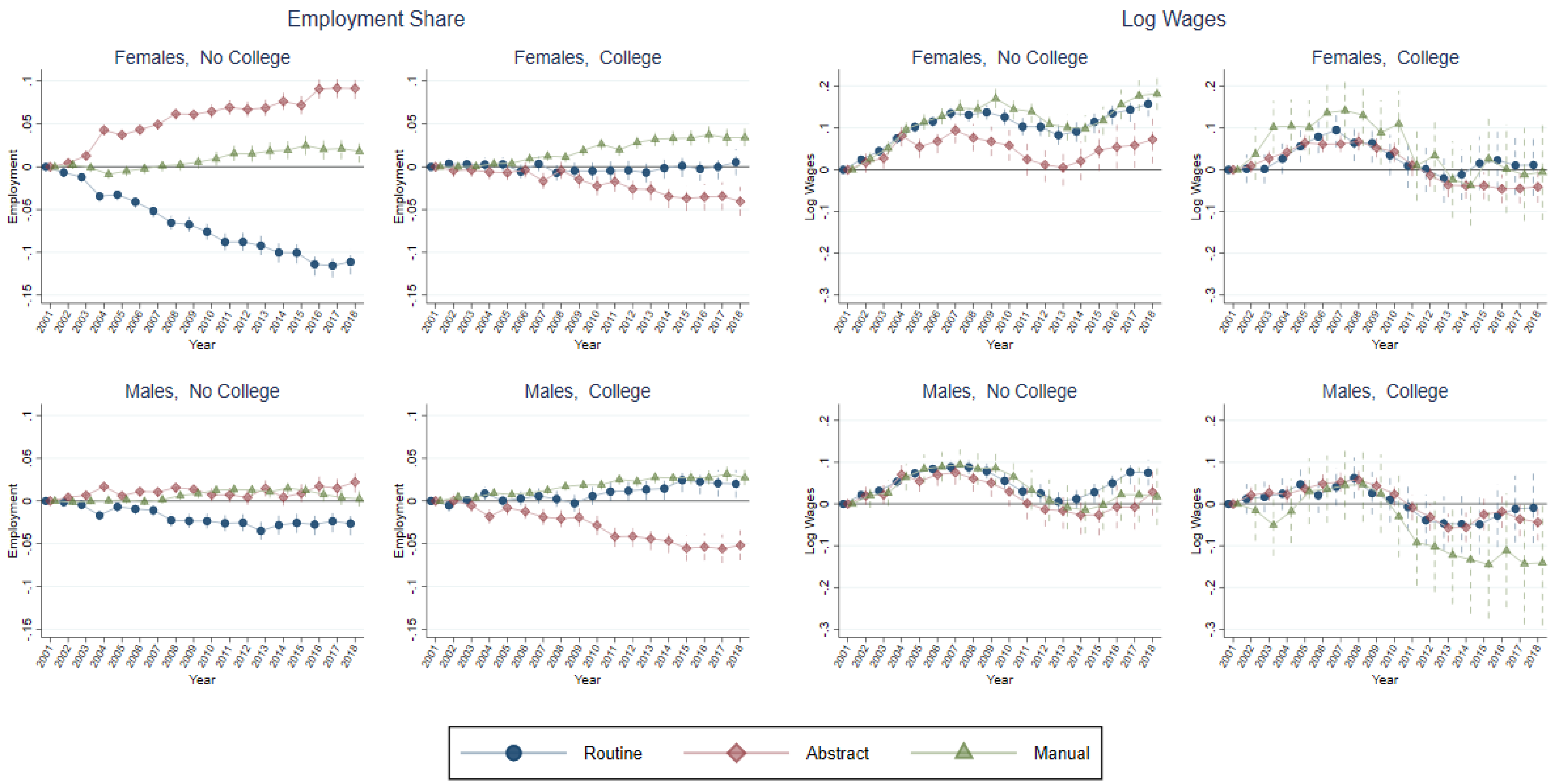
Figure 6. Age Polynomials from the Employment and Wage Regressions



Source: LFS and authors’ calculations.

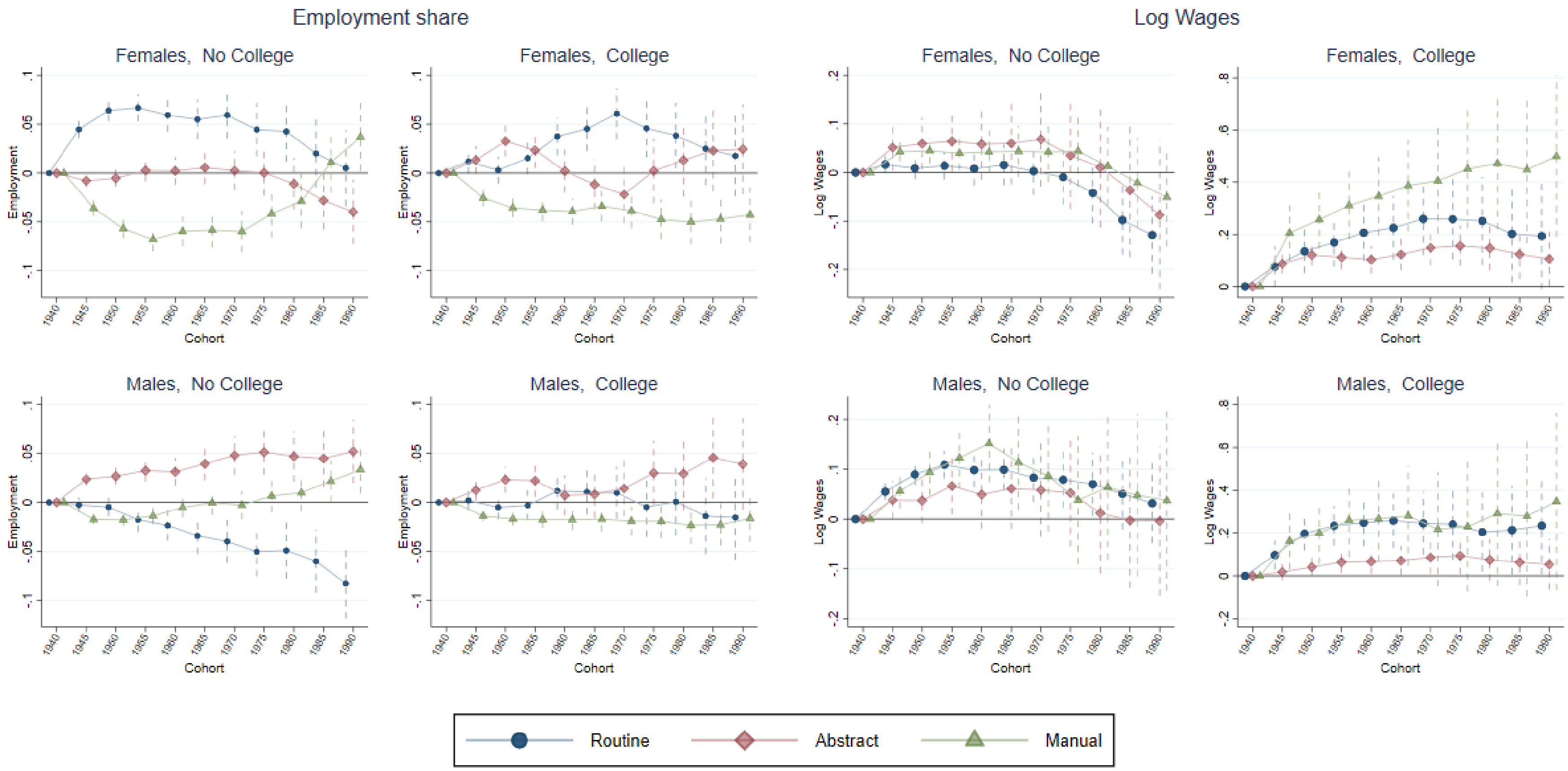
Note: In the left panel, each line represents the predicted share of employment in a given occupation over age by worker group, as obtained from the estimated coefficients of the age polynomial of the linear regression in (1). In the right panel, each line represents the predicted wage for workers employed in a given occupation over age by worker group, as obtained from the estimated coefficients of the age polynomial of the linear regression in (2).

Figure 7. Year Effects from the Employment and Wage Regressions



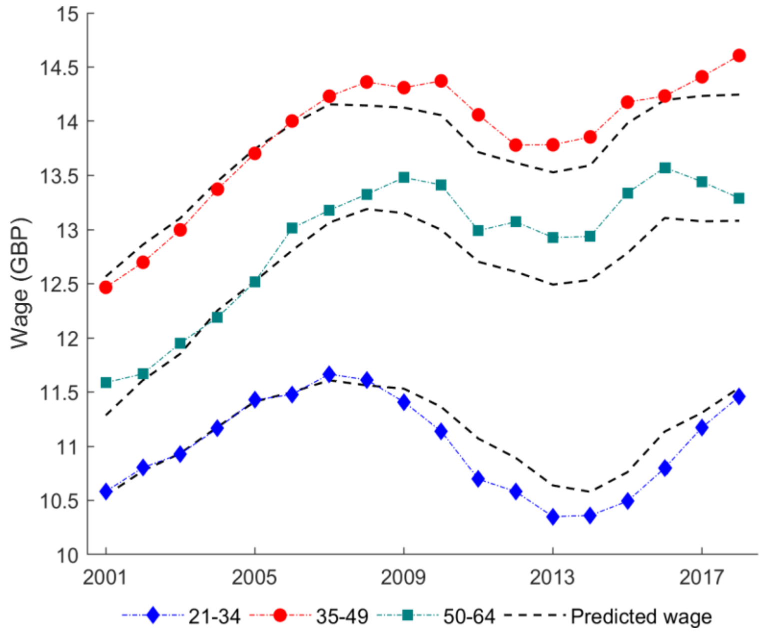
Source: LFS and authors' calculations.
Note: The four left-hand side panels report the estimated coefficients of the year effects from the employment regressions. The four right-hand side panels report the estimated coefficients of the year effects from the wage regressions. The baseline cohort is the 5-year cohort born between 1940 and 1944. The bars represent 95% confidence intervals based on robust standard errors.

Figure 8. Cohort Effects from the Employment and Wage Regressions



Source: LFS and authors' calculations.
Note: The four left-hand side panels report the estimated coefficients of the cohort effects from the employment regressions. The four right-hand side panels report the estimated coefficients of the cohort effects from the wage regressions. The baseline cohort is the 5-year cohort born between 1940 and 1944. The bars represent 95% confidence intervals based on robust standard errors.

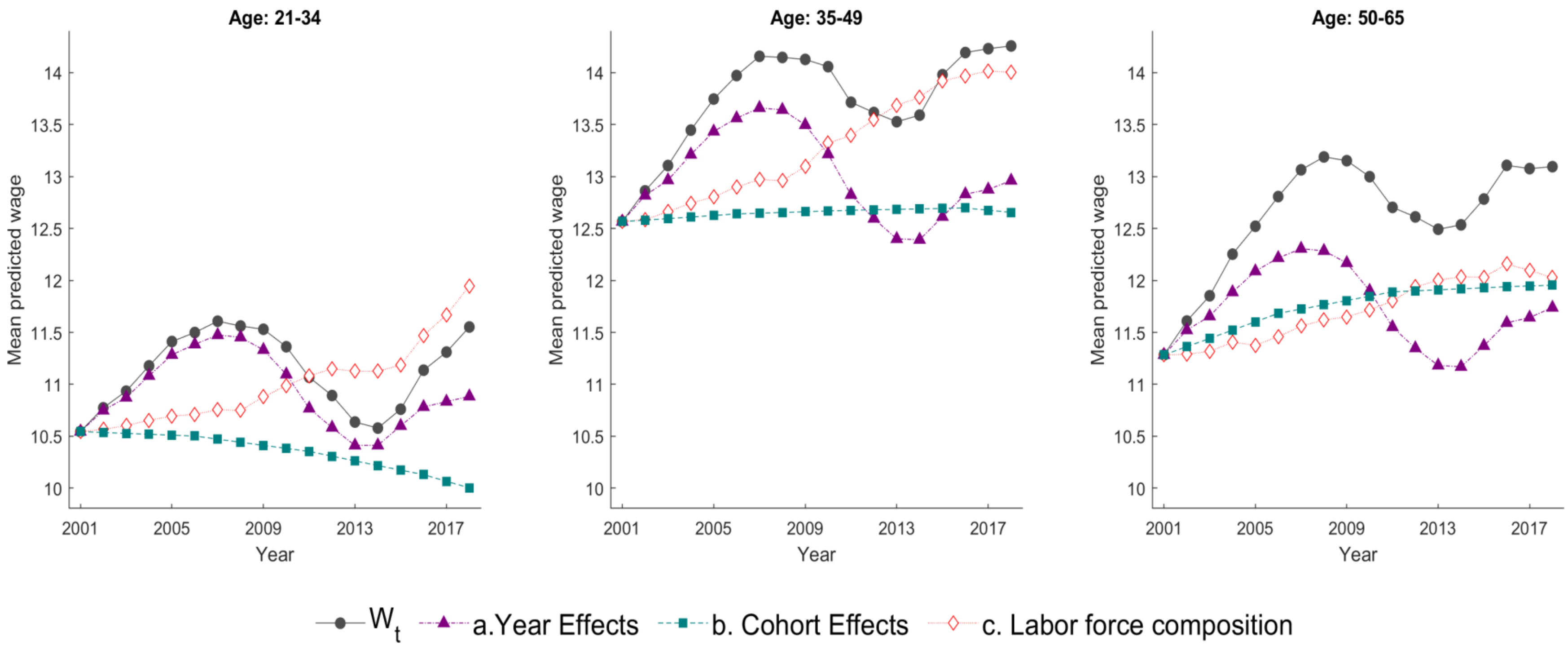
Figure 9. Empirical and Predicted Average Wages by Age Group



Source: LFS and authors' calculations.

Note: The markers report the raw average hourly wage (at 2010 prices) for each age group from the LFS. The black dashed lines report the predicted wages for the age group to which they are most closely aligned, computed through the predicted shares and wages in each occupation for each worker group, as described in (3).

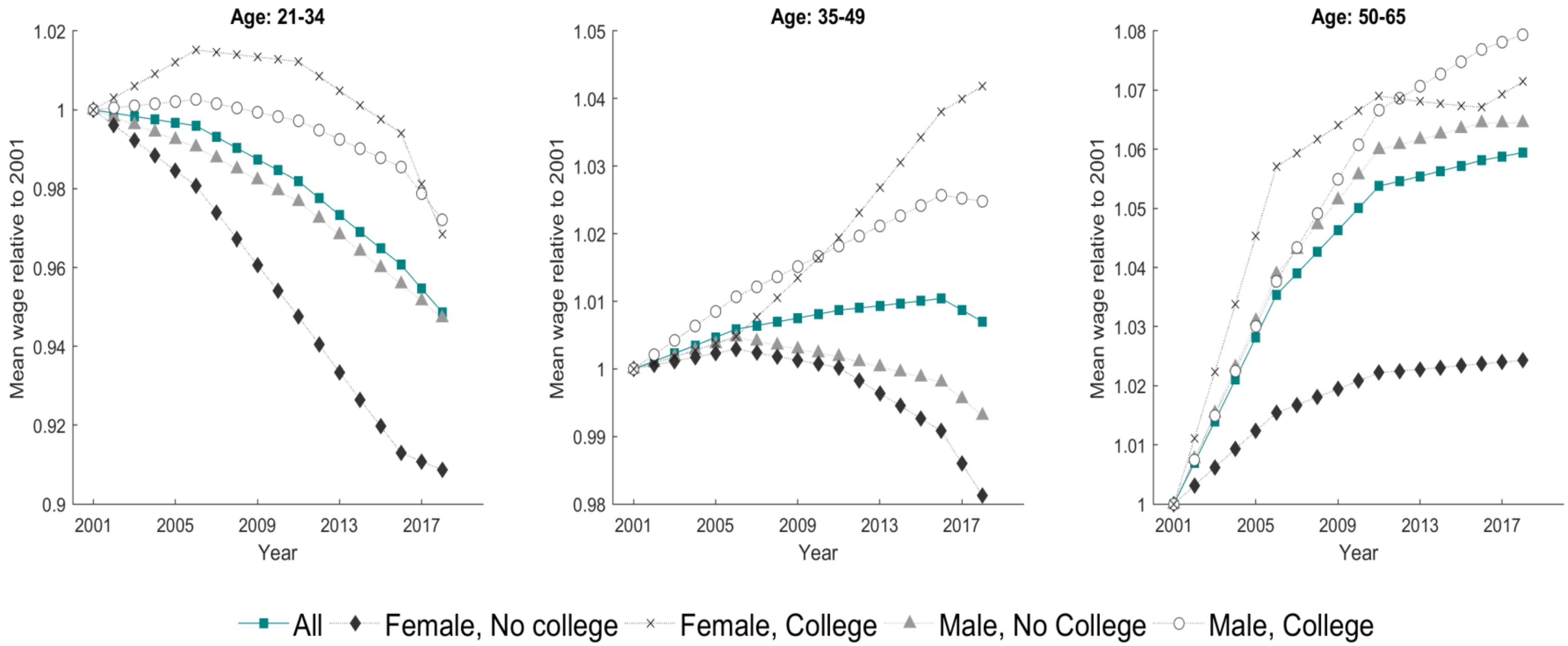
Figure 10. Decomposition of Average Wage by Age Group into Year, Cohort Effects and Labor Market Composition



Source: LFS and authors' calculations.

Note: The solid black circles report the full predicted wage in each age group computed following (3). The other markers report counterfactual wage series where only a single set of factors varies over time. The purple triangles represent the year effects-only wage series. The green squares report the cohort effects-only wage series. The red empty diamonds report the labor force composition-only wage series.

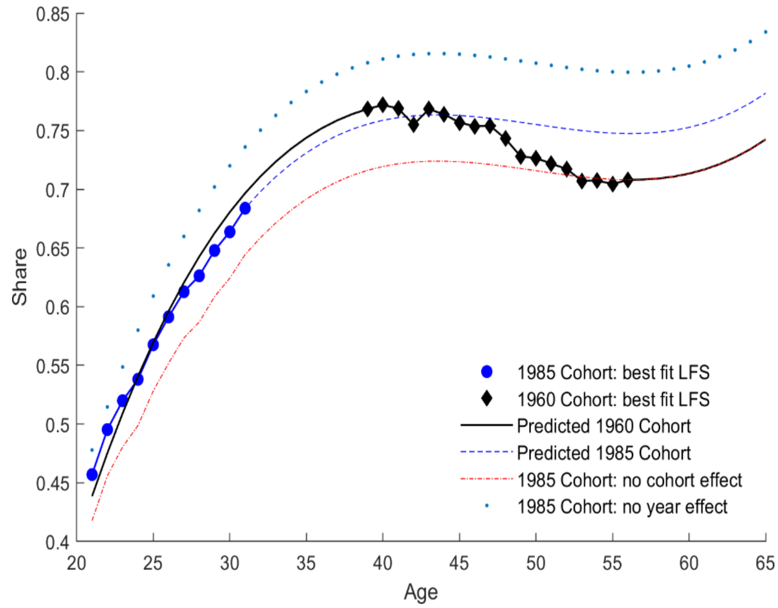
Figure 11. Cohort Effects Component of Average Wage by Education and Gender Across Age Groups, Relative to 2001



Source: LFS and authors' calculations.

Note: Each set of markers reports the cohort effects-only counterfactual wage series for a given group of workers within an age group. All series are normalized with respect to their 2001 value. The green squares report the average wage for all workers. Triangles report the wage for non-college males, diamonds for non-college females, empty circles for college-educated males, and crosses for college-educated females.

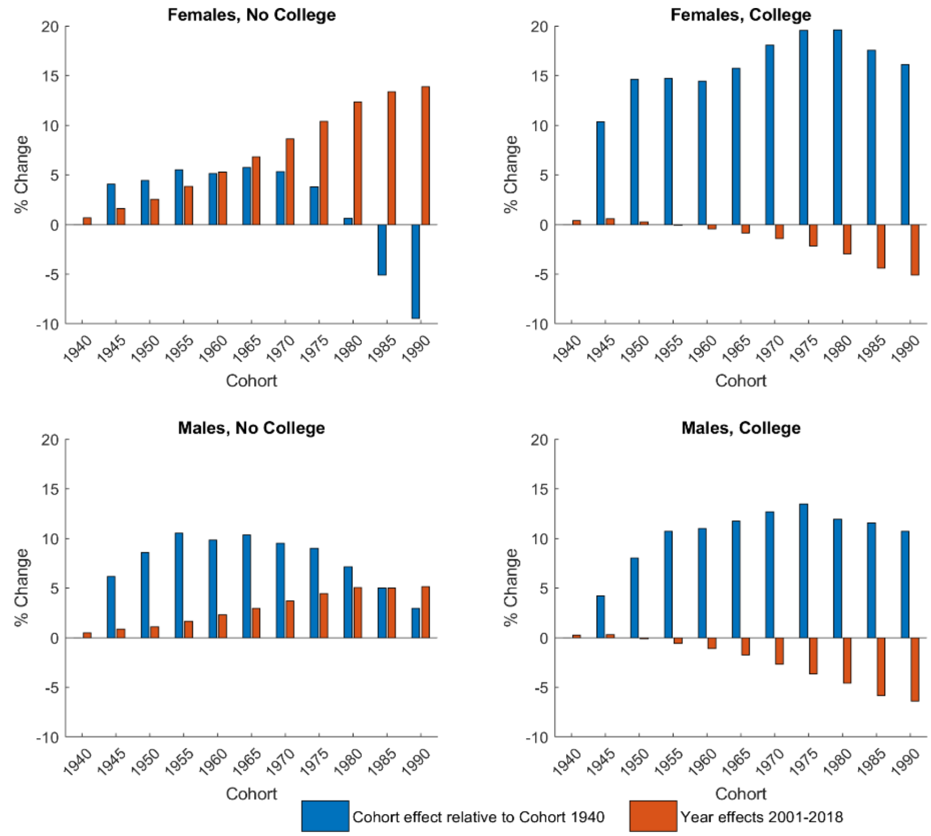
Figure 12. Best-Fit Share of Abstract Occupations for College-Educated Males: Comparison Between Cohort 1985 and Cohort 1960



Source: LFS and authors' calculations.

Note: The blue circles and black diamonds report the estimated share of college-educated males in abstract jobs for Cohorts 1985 and 1960, respectively, over the life-cycle for the years and ages included in the LFS. The dashed blue and solid black lines report the projected path of those shares for the year-age combinations not included in the LFS. The red dash-dot line reports the share for Cohort 1985 if it had the same cohort effect as Cohort 1960. The dotted blue line reports the share for Cohort 1985 if it did not include year effects.

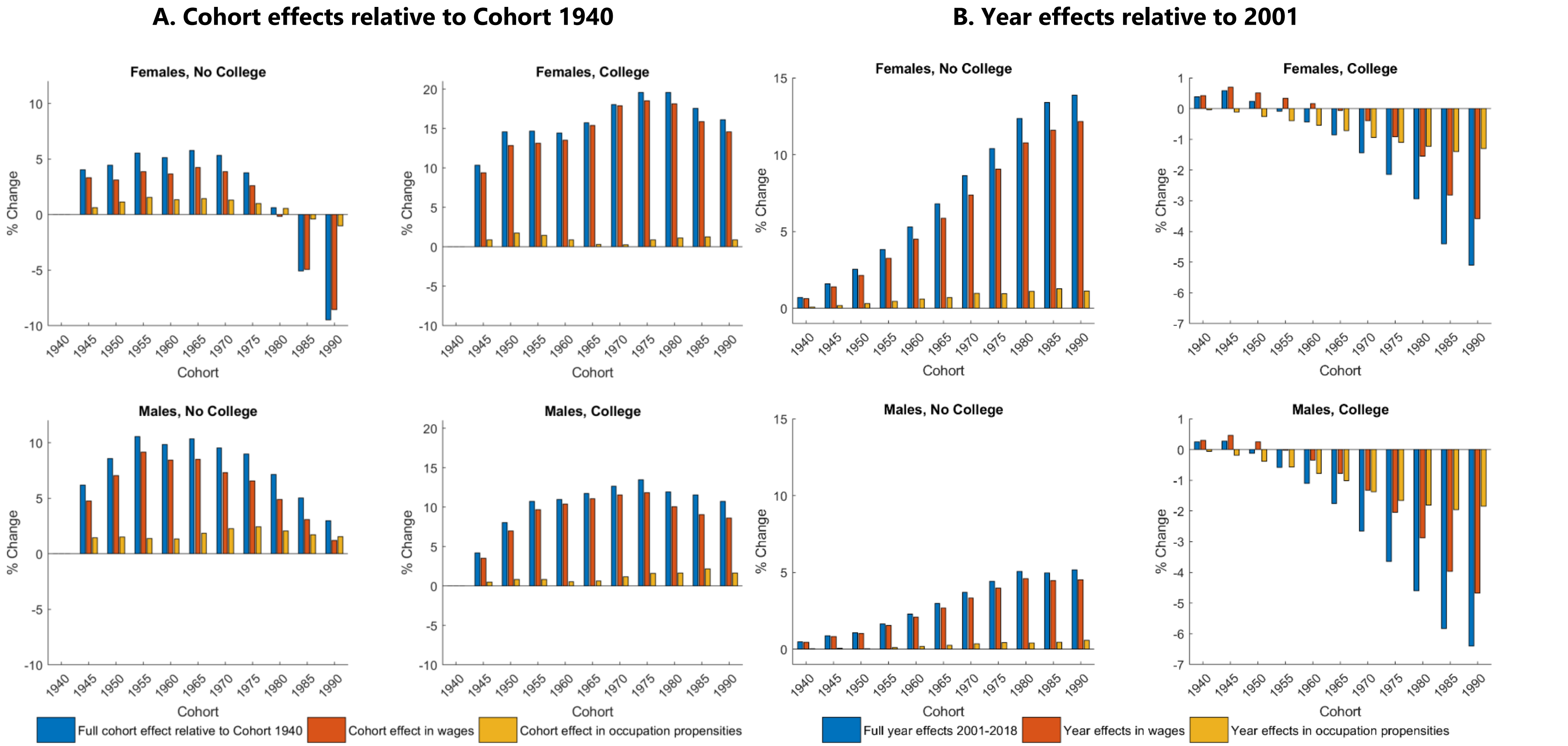
Figure 13. Contribution of Cohort Effects (Relative to Cohort 1940) and Year Effects (2001-2018) to the Present Value of Lifetime Earnings by Cohort and Demographic Group



Source: LFS and authors' calculations.

Note: The blue bars represent the percent contribution of the cohort effect (relative to Cohort 1940) for each cohort's average lifetime earnings. The orange bars represent the contribution of the year effects (relative to a fixed 2001 effect) for each cohort's average lifetime earnings.

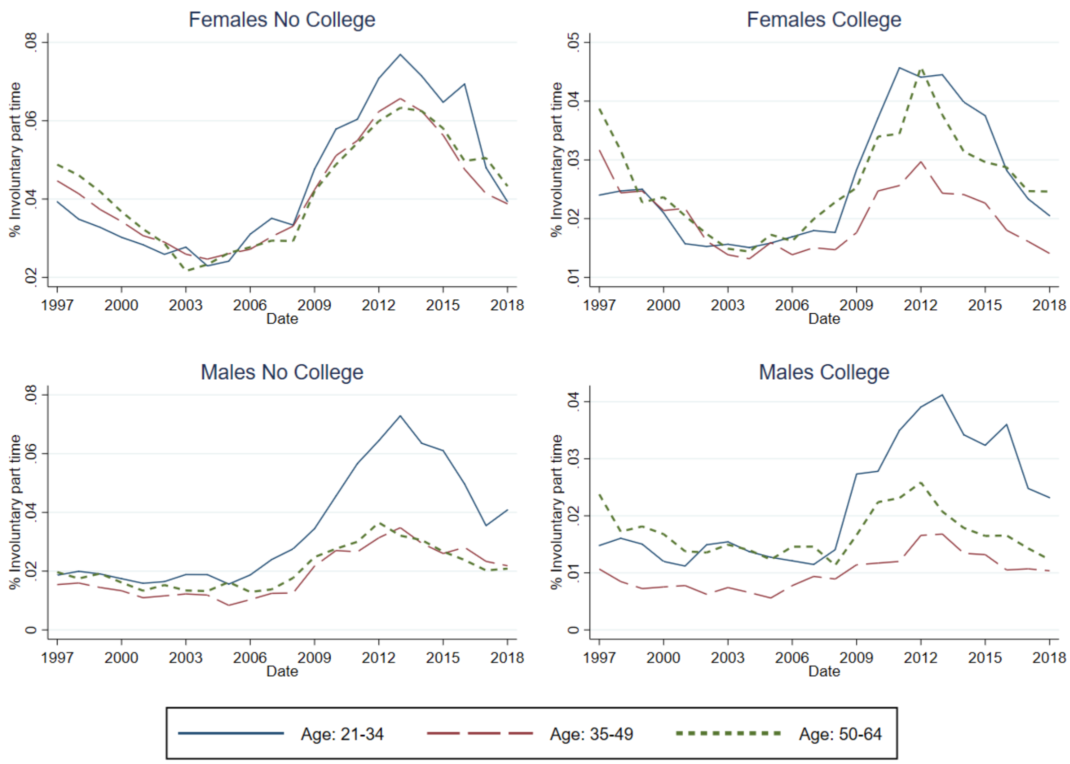
Figure 14. Contribution of Cohort Effects (Relative to Cohort 1940) and Year Effects (2001-2018) in Occupational Propensities and Wages to the Present Value of Lifetime Earnings by Cohort and Demographic Group



Source: LFS and authors' calculations.

Note: Panel A decomposes the total cohort effects (blue bars), as shown in Figure 13, into cohort effects in wages within each occupation (orange bars) and the employment share in each occupation (yellow bars). Panel B decomposes the total year effects (blue bars), as shown in Figure 13, into year effects in wages within each occupation (orange bars) and the employment share in each occupation (yellow bars).

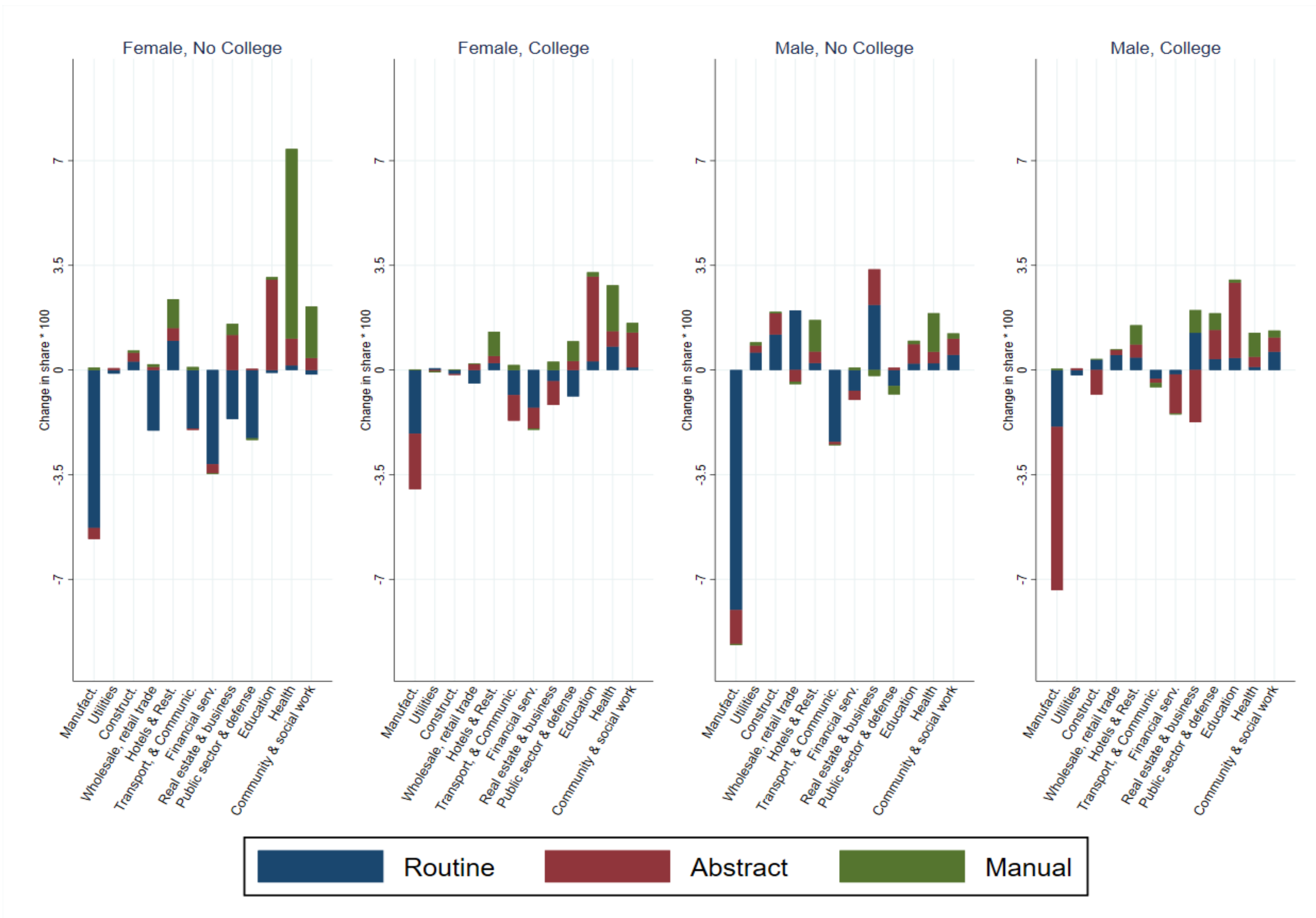
Figure 15. Share of Involuntary-Part Time Workers in Total Employment by Gender and Education Group, 1997-2018



Source: LFS and authors' calculations.

Note: Each line reports the fraction involuntary part-time workers of among all employed workers for each age group by gender and education.

Figure 16. Changes in Industries’ Employment Shares by Occupation Types Across Worker Groups for Young Workers, 2002-2017



Source: LFS and authors’ calculations.

Note: Each stacked bar reports the total change in employment share of each industry for the respective worker group aged 21-34. The colors represent the part of the change accounted for by each occupation type. The following industries have been excluded due to their small share of the total workforce: Agriculture, Fishing, Mining, Private Households Services, Extra-territorial organizations.

TABLES

Table 1. Shares of Employment and Distribution Across Occupation Types by Worker Group: 2001 and 2018

Worker Group		Labor Force Share		Occupation Shares					
				Routine		Abstract		Manual	
Gender	Education	2001	2018	2001	2018	2001	2018	2001	2018
Female	No College	32.43	24.12	55.50	44.67	18.42	25.88	25.78	28.98
Female	College	13.63	23.19	21.49	21.15	71.61	69.53	6.74	9.06
Male	No College	38.24	30.52	62.52	56.68	25.37	30.05	10.68	11.61
Male	College	15.70	22.17	22.39	23.38	72.72	69.77	4.13	5.87

Source: LFS and authors' calculations.

Note: Each row reports the share of the total labor force and the distribution of occupations across the three types for each gender-education group in 2001 and 2018.

Table 2. Contribution of Each Worker Group to the Total Change in the Employment Share by Occupation

		Routine			
Gender	Education	Total	Composition	Propensity	Interaction
Female	No College	-7.23	-4.61	-3.51	0.90
Female	College	1.97	2.05	-0.05	-0.03
Male	No College	-6.61	-4.83	-2.23	0.45
Male	College	1.67	1.45	0.16	0.06
		Abstract			
		Total	Composition	Propensity	Interaction
Female	No College	0.27	-1.53	2.42	-0.62
Female	College	6.36	6.85	-0.28	-0.20
Male	No College	-0.53	-1.96	1.79	-0.36
Male	College	4.05	4.71	-0.46	-0.19
		Manual			
		Total	Composition	Propensity	Interaction
Female	No College	-1.37	-2.14	1.04	-0.27
Female	College	1.18	0.64	0.32	0.22
Male	No College	-0.54	-0.82	0.36	-0.07
Male	College	0.65	0.27	0.27	0.11

Source: LFS and authors' calculations.

Note: The panels report the total contributions of each worker group to the change in the share of the respective occupation type between 2001 and 2018, as well as the breakdown into the composition and propensity components and their interaction as described in Section II.

Table 3. Change in Wage Gap of Young Workers Relative to Prime-Age and Old Workers: Actual Values and Counterfactuals

	$\Delta(w_{35\text{-}49}\text{-}w_{21\text{-}34})$	$\Delta(w_{50\text{-}64}\text{-}w_{21\text{-}34})$
LFS Δ 2001-2018	1.263	0.825
Best Fit Δ 2001-2018	0.684	0.801
Δ Year Effects	0.053	0.112
Δ Cohort Effects	0.633	1.210
Δ Composition	0.036	-0.658

Source: LFS and authors' calculations.

Note: The first row reports the actual change in the average wage gap between the age groups 21-34 and 35-49 (first column) and 50-64 (second column). The second row reports the change in the gap explained by the set of employment and wage regressions, computed following (3). The following line report the change that is explained by each component: year effects, cohort effects, and composition of the labor force.

Table 4. Top 5 Falling Routine Occupations, Top 5 Growing Abstract and Manual Occupations for Workers Between the Ages of 21 and 30

Routine
Top 5 Falling Occupations 2002-2017

Males: Occupation	Males: Change in Share (p.p.)	Females: Occupation	Females: Change in Share (p.p.)
9149 Other goods handling and storage occupations n.e.c.	-0.92	4215 Personal assistants and other secretaries	-2.18
9211 Postal workers, mail sorters, messengers, couriers	-0.71	4122 Accounts and wages clerks, book-keepers, other financial clerks	-1.24
5315 Carpenters and joiners	-0.64	4123 Counter clerks	-1.06
5231 Motor mechanics, auto engineers	-0.55	7111 Sales and retail assistants	-1.04
3542 Sales representatives	-0.51	7112 Retail cashiers and check-out operators	-0.77

Abstract
Top 5 Growing Occupations 2002-2017

Males: Occupation	Males: Change in Share (p.p.)	Females: Occupation	Females: Change in Share (p.p.)
3539 Business and related associate professionals n.e.c.	0.61	2315 Primary and nursery education teaching professionals	1.47
2315 Primary and nursery education teaching professionals	0.57	6124 Educational assistants	1.03
2132 Software professionals	0.54	6121 Nursery nurses	0.78
2314 Secondary education teaching professionals	0.50	3232 Housing and welfare officers	0.69
1135 Personnel, training and industrial relations manager	0.34	2319 Teaching professionals in n.e.c.	0.66

Manual
Top 5 Growing Occupations 2002-2017

Males: Occupation	Males: Change in Share (p.p.)	Females: Occupation	Females: Change in Share (p.p.)
6115 Care assistants and home carers	0.63	6111 Nursing auxiliaries and assistants	1.02
9223 Kitchen and catering assistants	0.29	6115 Care assistants and home carers	0.94
6111 Nursing auxiliaries and assistants	0.27	6222 Beauticians and related occupations	0.53
3250 Legal associate professionals	0.23	6131 Veterinary nurses and related occupations	0.20
5434 Chefs, cooks	0.20	3520 Legal associate professionals	0.09

Source: LFS and authors' calculations.

Table 5. Top 5 Falling Routine Occupations, Top 5 Growing Abstract and Manual Occupations for Workers Between the Ages of 35 and 64

Routine

Top 5 Falling Occupations 2002-2017

Males Occupation	Change in Share (p.p.)	**Females** Occupation	Change in Share (p.p.)
5223 Metal working production and maintenance fitters	-0.63	4215 Personal assistants and other secretaries	-2.19
5221 Metal matching setters and setter-operators	-0.53	7111 Sales and retail assistants	-1.32
8211 Heavy goods vehicle drivers	-0.39	4122 Accounts and wages clerks, book-keepers, other financial clerks	-0.84
5231 Motor mechanics, auto engineers	-0.38	4216 Receptionists	-0.75
3542 Sales representatives	-0.37	7112 Retail cashiers and check-out operators	-0.60

Abstract

Top 5 Growing Occupations 2002-2017

Males Occupation	Change in Share (p.p.)	**Females** Occupation	Change in Share (p.p.)
2132 Software professionals	1.30	6124 Educational assistants	1.30
1136 Information and communication technology managers	0.77	1136 Information and communication technology managers	0.77
1131 Financial managers and chartered secretaries	0.56	3211 Nurses	0.70
1122 Managers in construction	0.47	1239 Managers and propietors in other services n.e.c.	0.61
1135 Personnel, training and industrial relations manager	0.38	3539 Business and related associate professionals in n.e.c.	0.49

Top 5 Growing Occupations 2002-2017

Males Occupation	Change in Share (p.p.)	**Females** Occupation	Change in Share (p.p.)
6115 Care assistants and home carers	0.36	3520 Legal associate professionals	0.26
5434 Chefs, cooks	0.20	6139 Animal care occupations n.e.c.	0.24
5113 Gardeners and groundsmen	0.12	6222 Beauticians and related occupations	0.23
9241 Security guards and related occupations	0.12	6115 Care assistants and home carers	0.22
9223 Kitchen and catering assistants	0.12	3443 Fitness instructors	0.19

Source: LFS and authors' calculations.

ANNEX 1. Data Preparation and Occupational Categories

A key step entailed merging the UK occupational classifications with US-based categorizations, such as that of Cortes et al. (2016) and "task content" information from Autor et al. (2003). The LFS uses three different occupation classifications from 1994 to 2018: SOC 1990, SOC 2000, and SOC 2010 (the latter two are not the same as the BLS SOC for the US). We experimented with ways to create a consistent set of mappings by forming clusters of occupations for the SOC2000 and SOC2010 based on frequency distributions of the two occupations in a given wave of the LFS that provides both classifications. A similar mapping between SOC 1990 and SOC 2000 is not as straightforward because changes between the two classifications was more substantial. However, the step from SOC1990 to SOC2000 created large discontinuities at the aggregate level in the share of workers in each occupation type. Moreover, all LFS waves using the SOC2010 also provide a double-coded version of the worker's occupation variable using the SOC2000. We ultimately decided to only work with the period 2001-2018, using the double-coded SOC2000 variable after 2011.

The original task content measures are based on US occupation classifications (either US SOC or US Census). To address these issues, we have relied on a set of cross-walks. The Cortes et al. (2016) classification is based on the US census classification OCC 2000. To map it into the UKSOC 2000, we use the following crosswalks: OCC 2000 → US SOC 2000 → US SOC 2010 → ISCO 08 → UK SOC 2010 → UK SOC 2000. For the Autor and Dorn (2013) variables, which were in the US Census OCC1990 classification, we followed the mapping OCC 1990 → OCC 2000 → US SOC 2000 → US SOC 2010 → ISCO 08 → UK SOC 2010 → UKSOC2000. For the US crosswalks, when multiple occupations were combined, we used simple averages. When moving from the UK SOC 2010 to UK SOC 2000 we weighted the observations by the employment share in each UKSOC 2010 occupation, using the 2011q1 wave. We then assigned each UKSOC 2000 occupation to the occupation category with the highest share. For example, among workers employed in occupation *A* under UKSOC 2000, suppose that 80 percent are coded as employed in occupation α from UKSOC2010 and 20 percent in β. Furthermore, while α is routine, β is manual. In this case, we code occupation *A* as routine.

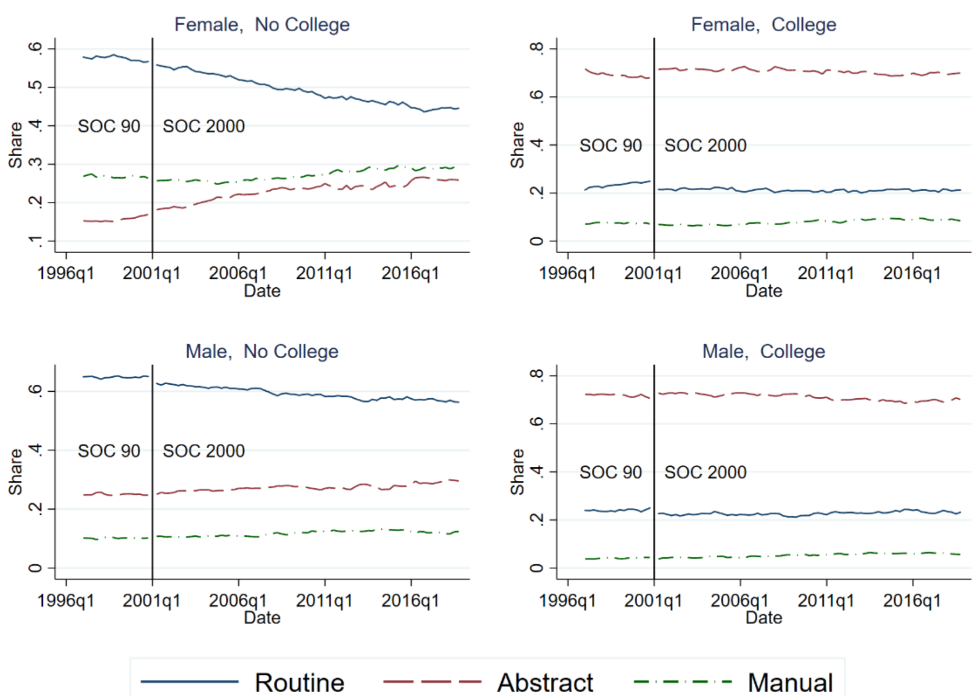
When attempting to use the data from the UK SOC 1990 we used the following mapping: ISCO 08 → ISCO 88 → ISCO 88 (COM) → SOC 1990. These extensive cross-walks imply some degree of approximation compared to the original task content dataset and a discontinuity in the aggregate statistics using the LFS. However, the essence of the information is very similar. Figure AI.1 shows how the SOC1990 compares to the SOC2000 over time and across demographic groups. When looking at aggregate measures (e.g., the percent of routine jobs in the economy) the discrete jump coming from the switch from SOC 1990 to SOC 2000 can be addressed through a simple rebasing of the variable from 1997 to 2000. However, when the level of analysis is narrowed (i.e., cohort-year-gender-education level) there is no straightforward adjustment. We thus limited the analysis to the period 2001-2018.

We also made some ad-hoc adjustments to some individual correspondences. In these cases, we used as a further source of comparison the non-unique occupational mapping provided by Dickerson et al. (2012) using the word-based matching software CASCOT.[36] The authors used the software to match descriptions of UK jobs with those of US jobs from the O*NET database. The adjustments made in this way are:

- UK SOC 2010 9232 was originally paired with ISCO 08 9613, which in turn was originally paired with US SOC 373019, which has no information on O*NET. We thus paired it with 474051 based on CASCOT information from Dickerson et al. (2012).

- UK SOC 2010 3561 and 3565 were originally paired with ISCO 3359 which was originally paired with 452011 (agricultural inspectors), but the original UK SOC occupations resemble more civil sector clerks. We thus repaired them with the ISCO 08 occupations corresponding to the US SOC 2010 codes that are matched with them in the CASCOT-based mapping from Dickerson et al. (2012).

Figure A1.1. Share of Routine, Abstract, and Manual Occupation by Worker Group 1996-2018



Source: LFS and authors' calculations. The figures plot time series from 1996 onwards.
Note: The data for the period 1996-2000 is constructed using the SOC1990 classification. For some categories, the switch from SOC1990 to SOC2000 creates a discrete jump in the fraction of workers in each occupation.

[36] We thank Prof. Rob Wilson from the Warwick Institute for Employment Research for sharing this mapping with us.

ANNEX 2. Occupational Categorization Measures

We first check to see alignment between our occupational categories and the RTI index constructed by Autor et al. (2003). The RTI is calculated using the task-content measures produced through the 1977 US Dictionary of Occupational Titles. The formula is RTI=Log(Routine Task) – Log(Abstract Task) – Log(Manual Task). Table AII.1 shows that the categorization is overall well aligned with routinization measured through the RTI.

Table A2.1. Summary Statistics of Routine Task Index by Occupation Type in 2001

	Routine Task Index							
	Males				Females			
	Mean	Median	25th pct.	75th pct.	Mean	Median	25th pct.	75th pct.
Routine	0.72	0.56	-0.31	1.61	2.35	2.51	0.81	3.34
Abstract	-0.03	-0.45	-0.65	0.53	-0.12	-0.46	-1.15	0.67
Manual	0.06	0.09	-0.30	0.67	0.45	0.32	-0.27	0.96

Source: LFS and authors' calculations.
Note: Each line reports the mean, median, 25th and 75th percentiles of the distribution of the RTI across all occupations in each category, separately for males and female.

Description of Alternative Occupational Categorization

As a robustness check, we classify occupations into the routine, manual, and abstract categories following Bhalotra and Fernández (2018). In particular, we merge the UK SOC 2000 occupation with task content measures computed by Autor and Dorn (2013) from the Dictionary of Occupational Titles 1977. We classify each occupation according to which category its task content is in the highest percentile relative to the other occupations.

First, we calculate the percentile corresponding to each occupation's value in the distribution of each task component—routine, manual, and abstract. Because we do this for each of the task components, every occupation classification has three different percentiles: routine, manual, and abstract. This procedure informs us of where each occupation stands relative to the others regarding the content of each type of task. We then assign each occupation to the category corresponding to its highest percentile. Because percentiles range from 0 to 100, they are comparable across categories. For instance, if an occupation is in the 90th percentile for manual, the 70th for routine, and 23rd for abstract, we categorize it as a manual occupation.

This procedure categorizes occupations according to how they compare to each other in their task components. They are no longer categorized according to their "absolute" task content alone. Like any other classification choice, it contains a degree of arbitrariness and noise.

Comparison with Baseline Categorization

Table A2.2 shows the cross-distribution of workers in the two occupational groupings for the first and last years of the sample. Overall, the two methods are consistent, and the majority of workers remain in the same category. By construction, the alternative method implies a larger share of manual occupations. Therefore, the main transition is from routine and abstract into manual, especially for non-college males. However, there is also a substantial reclassification of jobs from routine to abstract for college-educated workers. Table A2.3 compares the breakdown across industries to check whether the reclassification was particularly concentrated in some sectors. The main significant changes are in the hotels and restaurants, where the share of manual jobs falls in favor of abstract ones, and in manufacturing, where the share of routine employment falls by 20 percentage points. Analysis showing that the baseline results about job polarization trends at the education and gender level hold under the alternative method are available upon request.

Table A2.2. Cross-Distribution of Baseline and Alternative Categorizations for 2001 and 2018 by Worker Groups

2001q2-2002q1

Female, No College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	68.7	25.3	6	100
Abstract	5.7	91.4	2.8	100
Manual	10.9	5.7	83.5	100
Total	41.8	32.6	25.6	100

Female, College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	63.8	32.1	4.2	100
Abstract	4.9	81.5	13.5	100
Manual	9.6	11.4	79	100
Total	17.9	66.4	15.7	100

Male, No College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	47.1	18.4	34.5	100
Abstract	8.9	86.8	4.3	100
Manual	10.5	5.7	83.7	100
Total	33.1	34.8	32.1	100

Male, College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	45.1	41	13.9	100
Abstract	6	89.3	4.7	100
Manual	4.4	10.3	85.3	100
Total	14.6	75.2	10.2	100

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Female, No College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	62.6	31	6.4	100
Abstract	5	91	3.9	100
Manual	10.2	7.2	82.6	100
Total	32.4	38.5	29.2	100

Female, College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	58.9	36.1	5	100
Abstract	5.3	84	10.7	100
Manual	7.2	12.3	80.6	100
Total	17.4	66	16.6	100

Male, No College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	41.2	20.5	38.3	100
Abstract	7.4	88.1	4.6	100
Manual	14.9	5.7	79.4	100
Total	28.3	37.5	34.2	100

Male, College

	Alternative			
	Routine	Abstract	Manual	Total
Baseline				
Routine	43.3	36.7	20	100
Abstract	6.1	88.5	5.4	100
Manual	8.2	10.7	81.1	100
Total	15.7	70	14.3	100

Source: LFS and authors' calculations.

Note: Using the stated quarters of the LFS each panel shows the distribution of workers in each occupation under the baseline categorization across the occupation categories of the alternative categorization.

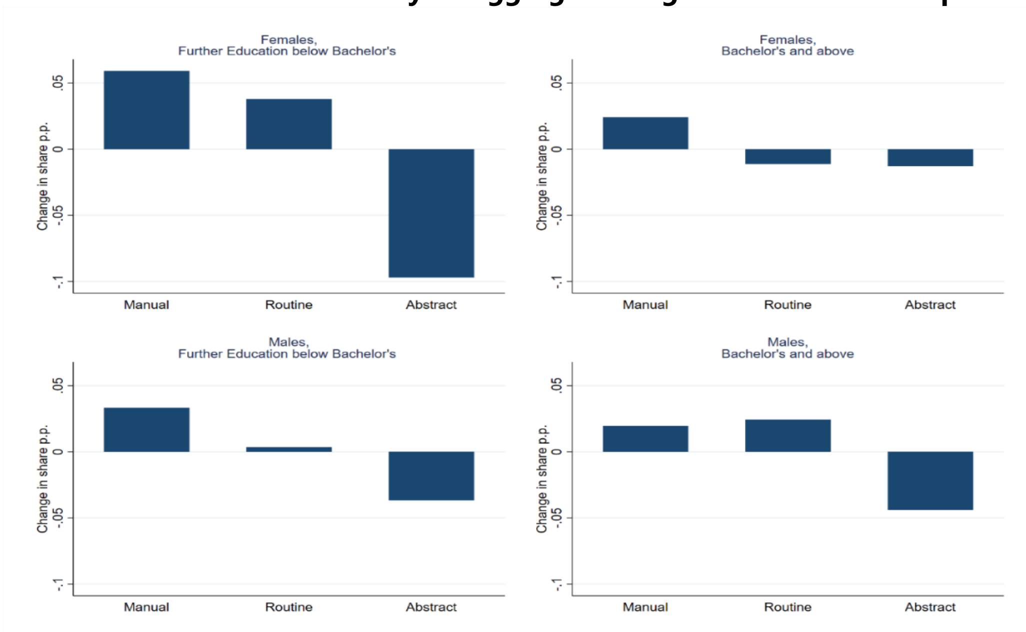
Table A2.3. Occupational Distribution in Each Industry Based on Baseline and Alternative Occupation Categorizations in 2001

	Routine		Abstract		Manual	
INDUSTRY	**Baseline**	**Altern.**	**Baseline**	**Altern.**	**Baseline**	**Altern.**
Agriculture, hunting & forestry	13.95%	7.20%	13.67%	15.55%	31.71%	77.25%
Construction	70.81%	32.18%	27.67%	30.62%	1.46%	37.20%
Education	10.33%	11.13%	74.30%	57.58%	15.29%	30.57%
Electricity gas & water supply	62.05%	42.62%	35.23%	37.55%	2.52%	19.83%
Extra-territorial organisations, and bodies	27.32%	25.03%	59.29%	59.23%	6.69%	9.04%
Financial intermediation	57.52%	41.68%	41.36%	56.16%	1.13%	2.16%
Fishing	19.94%	7.05%	19.03%	26.53%	60.08%	66.42%
Health & social work	17.68%	21.11%	46.33%	42.08%	35.98%	35.65%
Hotels & restaurants	14.01%	23.01%	25.00%	40.48%	60.96%	36.49%
Manufacturing	70.38%	51.33%	28.17%	34.39%	1.43%	14.27%
Mining, quarrying	61.02%	27.54%	37.60%	38.39%	1.38%	34.08%
Other community, social & personal	28.68%	27.79%	40.88%	40.86%	30.25%	31.21%
Private households with employed persons	4.25%	1.83%	4.13%	4.33%	91.62%	93.84%
Public administration & defense	42.79%	35.40%	32.69%	36.11%	22.94%	26.89%
Real estate, renting & business activities	35.38%	26.26%	51.94%	58.11%	12.62%	15.63%
Transport, storage & communication	74.74%	26.17%	19.94%	35.64%	5.30%	38.18%
Wholesale, retail & motor trade	72.90%	31.32%	24.16%	57.86%	2.88%	10.82%

Source: LFS and authors' calculations.

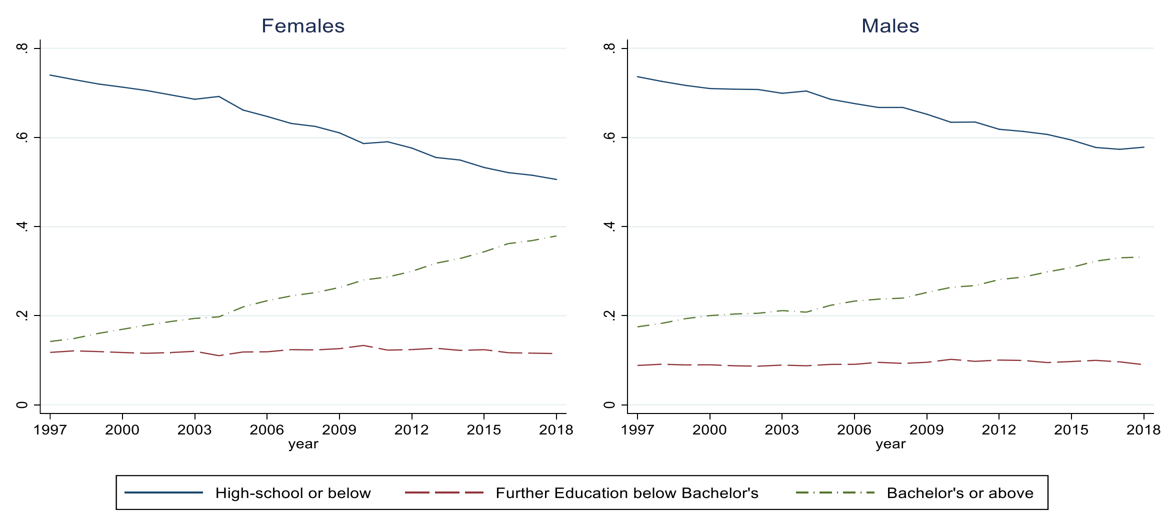
ANNEX 3. Disaggregating the College Group

Figure A3.1. Change in Employment Shares of Manual, Routine, and Abstract Occupations Between 2001 and 2018 by Disaggregated High-Skill Worker Groups



Source: LFS and authors' calculations.
Note: The blue bars report the change in the share of employment in each occupation group between 2001 and 2018 by gender and education group: those with further education below Bachelor's level and those with a Bachelor's degree or above.

Figure A3.2. Change in Share of Employment for Workers by Disaggregated Education Level, 1997-2018



Source: LFS and authors' calculations.
Note: Each line reports the share of employed workers in each education group by gender over the period 1997-2001.