The Evolution of Prices and Quantities of Occupational Human Capital *

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Abstract

I estimate the evolution of prices and quantities of human capital in occupational groups specializing in abstract, routine, and manual tasks to examine the explanations for rising U.S. wage inequality. To quantify changes in prices and quantities of occupation-specific human capital, I use a *flat spot* price identification method which exploits the wage changes for workers approaching retirement to infer the shifts in the prices of skills. Importantly, this method accommodates cohort quality changes over time, capturing the effects of shifts in the educational composition of workers in occupations as well as changes in the quality of education across generations. My results show that the price increased for the abstract group relative to manual and routine groups between 1970 and 2022. Conversely, the prices of human capital in manual and routine groups declined and were highly correlated. This evidence favours the hypothesis of skill-biased technical change (SBTC), which predicts the increase in the relative price of high-skill human capital. Furthermore, even within the abstract group, professional workers with relatively higher levels of training have disproportionately benefited from the changing relative demand for high-skill workers compared to workers in managerial and technician occupations, supporting the implications of the SBTC theory.

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1 Introduction

The rapid growth of wage inequality in the U.S. over the last four decades is characterized by a widening of educational wage differentials for workers with college education relative to less-educated workers and for workers with graduate degrees relative to undergraduate degree workers (Autor, Katz, and Kearney, 2008). Moreover, the inequality trends in the upper and lower tails of the wage distribution have diverged. Upper-tail inequality has been steadily rising, with the male 90/50 log hourly earnings ratio growing continuously at the rate of about 1 log point per year from 1980 to 2005. At the same time, lower-tail inequality has compressed as wages have grown faster at the bottom relative to the middle of the wage distribution, with the male 50/10 earnings ratio expanding in the first half of the 1980s but reversing course thereafter (Acemoglu and Autor, 2011).

Two leading explanations of these trends relate the observed changes in wage inequality to the non-linear effects of technological growth on different skill groups of workers. On the one hand, skill-biased technological change (SBTC) theory defines workers' skills by education and explains the overall expansion of the wage inequality by the increase in the relative demand for high-skill college-educated labour (Katz and Murphy, 1992, Autor, Katz, and Krueger, 1998, Carneiro and Lee, 2011). On the other hand, the routine-biased technical change (RBTC) theory focuses on the occupational tasks performed by workers. It suggests that due to technical changes and offshoring, the demand for high-skill abstract and low-skill manual occupational human capital has increased relative to the demand for middle-skill routine human capital. This shift is driving the divergence in wage inequality trends between the upper and lower parts of the wage distribution (Autor, Levy, and Murnane, 2003, Acemoglu and Autor, 2011, Goos and Manning, 2007).

As the wage is determined by both the price and the quantity of a worker's human capital stock, the growing wage gap between different skill groups of workers can be explained by changing relative prices or by changing relative quantities of human capital, neither of which are directly observed by researchers. Both SBTC and RBTC explanations predict that the observed trends in inequality are generated by changing relative prices of different human capital groups.

To estimate the trends in relative prices, the SBTC literature commonly employs composition adjustment methods to control for changes in the human capital supply, which assume that the human capital stocks within groups defined by workers' characteristics are constant over time.[3] Similarly, the RBTC literature often uses the Roy model of selection into occupation and assumes that there are no cohort effects in the population distribution of skill, or in the relationship between workers' ability and their occupational human capital.[4] In the context of SBTC, Bowlus and Robinson (2012) allow for across-cohort changes in the distribution of human capital and show that the growing wage gaps between workers with different education levels are driven primarily by changes in relative quantities of human capital, not relative prices. Given the potential importance of quality changes across cohorts, I reexamine the RBTC explanation of growing wage inequality by allowing for across-cohort changes in the human capital distribution.

To do so, I estimate the evolution of the price and quantity of human capital for abstract, routine, and manual occupational groups using the data from the U.S. March Current Population Survey (MCPS). I find that, between 1970 and 2022, the price of the routine and manual occupational groups declined by 18.6% and 38% respectively, while the price for the abstract group increased by 2.8%. I show that, since the early 1990s, the growth in the relative wage premium of the abstract group relative to the routine group was driven mainly by the growth in relative skill prices. In contrast, the rising wage premium of the manual group relative to the routine group can be attributed to the growth in the quantity of human capital in manual occupations.

Further, I show that within the abstract occupational group, the increase in the price is driven disproportionately by workers with the highest skill levels. Between 1970 and 2022, the price of professional workers with the highest average levels of training in abstract occupations increased by 8%, while the prices for managerial and technical occupations slightly declined. While this difference is not statistically significant due to a reduction in sample sizes compared to the main result, these findings are suggestive that the increase in the wage premium for high-skill documented in the previous literature was driven by an increase in the relative price of human

[3] For example, Katz and Murphy (1992) assume that the efficiency units of human capital remained constant within 320 groups defined by gender, education, and experience.

[4] Böhm (2020), Gottschalk, Green, and Sand (2015), Cortes (2016), and Cavaglia and Etheridge (2020) use Roy-model based identification strategies and document the increase in the prices of abstract and manual occupation groups relative to the routine group.

capital.[5] This result further corroborates that, over the last decades, technology increasingly benefited the productivity of workers at the top of the wage distribution.

My findings explain the growing wage inequality and the polarization of wages as a combination of different movements in the prices and quantities of occupational human capital. Inequality at the top of the wage distribution is driven by relative prices of human capital, which is consistent with the SBTC hypothesis. Inequality at the bottom of the wage distribution is driven by different forces. The prices of both manual and routine occupational groups declined, reflecting a decrease in the demand for routine and manual tasks relative to the supply. Instead, the rising wage premium of manual workers is explained by the increase in the quantity of manual human capital for later cohorts. These findings provide less support for the presence of RBTC which predicts that the rising relative price of manual human capital drives compression of wage inequality between routine and manual groups.

To estimate the price and quantity sequences, I adopt the flat spot identification approach developed in Heckman, Lochner, and Taber (1998) and Bowlus and Robinson (2012) for education-based human capital, and modify it to measure occupation-based human capital. The approach is based on the prediction that the life-cycle human capital profile exhibits a concave shape with a flat spot near the end of a worker's career over which the change in the hourly wage is generated by skill price fluctuations (Ben-Porath, 1967). The key advantage of this price identification approach is that it allows for cohort effects in the production and distribution of human capital. The observed shifts in the educational and occupational compositions of the workforce since the 1980s imply that the skill distribution of the population conditional on education and even initial skill levels have likely changed over my period of interest, and ignoring the across cohort changes in human capital stocks confounds the price change estimates.[6]

This paper proceeds in four sections. Section 2 explains how the flat spot price identifica-

[5] Autor et al. (2008) argue that, while the earnings of workers with postgraduate degrees were rising continuously since 1979, the earnings of college-only workers plateaued after 1987. More recently, Lindley and Machin (2016) document that postgraduates and college-only workers exhibited different wage trends, with the return to postgraduate education rising relative to the return for bachelor degrees.

[6] Carneiro and Lee (2011) and Hendricks and Schoellman (2018) find that the college enrollment rate increase leads to substantial changes in the average quality of college graduates' human capital. Bowlus and Robinson (2012) argue that the selection effect from the college enrollment rate change was accompanied by the technological improvement in human capital production function for college graduate cohorts, resulting in the human capital quality improvement of later cohorts of college graduates.

tion methodology can be applied to occupational groups and motivates the use of MCPS data. Section 3 discusses the results, including the estimates of the price and quantity series, and the implications of the identified trends for SBTC and RBTC explanations of the growing inequality. Section 4 concludes.

2 Methodology and Data

2.1 Methodology

The hourly wage earned by a worker employed in a certain occupation can be influenced by the quantity of occupation-specific skill they possess and by how the market values this skill. The period t hourly wage for a worker i of age a depends on their supplied stock of efficiency units of human capital specific to their broad occupational group o specializing in abstract, routine, or manual tasks $o = \{A,R,M\}$, $H_{i,t}^{o,a}$, and on the current efficiency unit price of occupational human capital P_t^o as follows

$$Wage_{i,t}^{o,a} = P_t^o \times H_{i,t}^{o,a}.$$

Therefore, observed changes in wages and wage inequality can be driven by shifts in the prices for an efficiency unit of occupational human capital, or by changes in worker's human capital stocks, neither of which are directly observed in the data. Since changes in wages driven by prices or quantities of human capital vary in their implications for the underlying causes of changes in wage inequality, it is important to separately identify the evolution of prices and quantities over time.

I identify occupational human capital price sequences by applying the flat spot price identification method of Heckman et al. (1998) and Bowlus and Robinson (2012). The method builds on the Ben-Porath (1967) human capital investment model, which predicts that as workers approach retirement the gains from human capital investment decline. Consequently, the life-cycle human capital profile exhibits a concave shape with a flat spot prior to retirement within which human capital levels are constant. Under this identification assumption workers in their flat spot age range a^* have stable stocks of human capital

$$E[lnH_{i,t}^{o,a*} - lnH_{i,t-1}^{o,a*-1}] = 0,$$

and the wage growth during the flat spot age range reflects the price change

$$E[lnW_{i,t}^{o,a*} - lnW_{i,t-1}^{o,a*-1}] = lnP_t^o - lnP_{t-1}^o.$$

The price change for an efficiency unit of human capital can therefore be identified from the average wage growth of workers in the age range of the flat spot of their human capital profile.[7]

The flat spot method identifies prices of human capital under three conditions. First, workers who belong to the same birth cohort and human capital type are assumed to have a stable human capital stock over the flat spot region. Second, the skill must be homogeneous within human capital groups.[8] Finally, the wage change for high-tenure workers reflects the market price change and is not driven by contractual issues between them and their employers.[9]

There are two additional issues associated with applying the flat spot price identification approach to occupation-based human capital. First, workers in different occupations do not have a well-defined labour market entry age. As a result, the relationship between the timing of the labour market entry and the flat spot age exploited in Bowlus and Robinson (2012) for different education groups is not well defined in the occupational human capital setting. The second issue relates to occupational switching and the stability of skill groups defined by occupations. While a worker's education level is generally fixed at later stages of the career, occupations are a product of endogenous selection over the life-cycle. The wage growth of workers in their flat spot age range in a synthetic cohort reflects the change in the price of occupational human capital only if composition effects due to workers switching occupations are negligible. These issues are discussed in Subsection 2.3 and Appendix C, B, and D, where I show that the effect of occupational

[7] Full details found in Bowlus and Robinson (2012) and Heckman et al. (1998).

[8] Appendix H uses the DOT data on task intensity across occupations to explore the age dynamics of the average intensity of abstract, routine, and manual tasks within broad occupational groups. It shows that workers, on average, specialize in their respective occupational tasks consistently over the flat spot age range.

[9] Appendix G explores the age dynamics of several non-pecuniary job characteristics like employer-provided health and pension plans for workers in different occupational groups and shows that contractual differences in these trends across occupation groups are unlikely to affect my results.

group switching behaviour on my estimates is limited.

The flat spot approach has an important advantage over alternative methods in estimating the price change over long-term horizons because it allows consistent estimation in the presence of cohort effects. For instance, estimation strategies based on the Roy model of selection require that the population distribution of abilities is stable over time and across different cohorts of workers. The mapping between workers' abilities and their occupational human capital stock is also required to be stable over the estimation period.[10] While these assumptions might hold in the short run, the presence of cohort effects in human capital production function documented in Bowlus and Robinson (2012) and Carneiro and Lee (2011) confound the long-run price change estimates.

2.2 Sample Construction and Statistics

Identification of the occupational human capital price series requires information about wages, labour supply, and occupational choices from a representative sample of workers. This information is accessible for U.S. workers in the March Current Population Survey, which offers the longest available data series on the U.S. labour force's social and economic indicators. The rich information about employment allows me to consistently control for the annual labour supply of workers and avoid issues concerning workers' selection into part-time jobs and retirement.[11]

Following Bowlus and Robinson (2012), I construct an hourly wage measure by dividing inflation-adjusted annual earnings by annual labour supply.[12] I focus on the sample of male workers between 30 and 64 years old who are employed full-time, full-year (FTFY), i.e. working 35-plus hours per week and 40-plus weeks per year. I exclude self-employed workers, workers without records of their occupation, annual earnings, or variables used to construct the measure of an-

[10] These strategies require an exclusion restriction that, after adding a control function (Böhm, 2020) or fixed effects (Cortes, 2016, and Cavaglia and Etheridge, 2020), the price change for a unit of human capital can be identified from the wage regression.

[11] An alternative data source that provides measures of income and supply of labour are the Merged Outgoing Rotation Group (MORG) samples. However, the number of weeks worked annually is available for only 12% of earners who report their earnings as an annual amount, which limits the potential to select individuals with strong labour market attachment.

[12] The annual labour supply is calculated as a product of weeks worked last year and hours usually worked per week last year since 1976 and as a product of weeks worked last year and hours worked last week before 1976.

nual hours worked. I use median hourly wages for the price series estimation to deal with the top-coded values. While the MCPS data are available starting from 1964, the occupational classification scheme in the 1960s is not sufficiently detailed. Therefore, I focus on the data beginning in 1971, when a more detailed occupational coding scheme is available.[13]

I sort workers following Acemoglu and Autor (2011) into abstract, routine, and manual occupation groups. This occupational grouping has been shown to preserve the relative ranking of occupational groups in terms of their task intensity and has been used consistently in the RBTC literature.[14] The sorting of workers is based on the 1990 CPS occupational classification. The abstract occupation group includes workers in managerial, professional, and technical occupations. The routine occupation group includes workers in sales, clerical, and administrative; and production, crafts, repair, and operative occupations. Finally, the manual occupation group includes workers in services occupations.

Figure 1 reports the shares of age, occupation, and education groups in the sample for each decade of data. Figure 1a shows that the sample is aging over the time frame, reflecting demographic trends in the U.S. Figure 1b shows evidence of the polarization of the occupational structure of the labour market, with the share of abstract and manual occupations growing, and the share of routine occupations declining. Figure 1c reflects the growing educational attainment of the population, with the increasing proportion of workers with at least some college dominating the market.

Figure 2 illustrates the evolution of the educational composition of the three occupation groups. Abstract occupations have been increasingly performed by the most educated group of workers, while less-educated workers have been crowded out of the abstract group into manual and routine occupation groups. Simultaneously, workers with some college or even with a bachelor's degree have increasingly substituted for high school dropouts and high school graduates

[13] To make occupational groups comparable across time I use a cross-walk between the 1990 occupational coding and occupational coding for 1972-1982, 1983-1991, 2003-2010, and 2011-2018 constructed by the Integrated Public Use Microdata Series (https://doi.org/10.18128/D030.V8.0). The results are robust to using alternative crosswalk based on Autor and Dorn (2013).

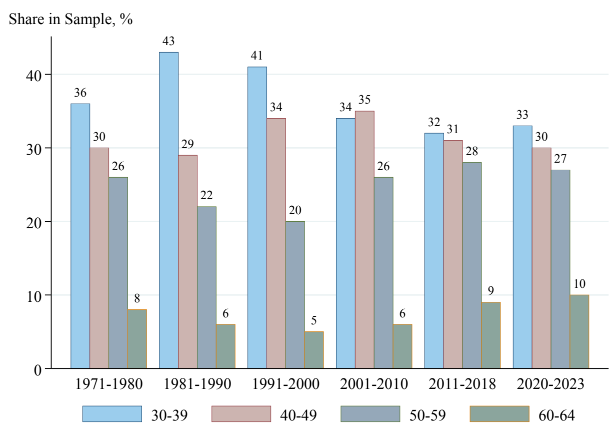
[14] For example, Beaudry et al. (2016), Böhm (2020), Cavaglia and Etheridge (2020), Cortes (2016) use a similar occupation grouping. Appendix H analyzes the average task intensity across occupation groups based on the the Dictionary of Occupational Titles (DOT) data. It shows that workers in each occupational group tend to specialize in tasks according to their classification: for example, the average intensity of abstract tasks is the highest in abstracts occupational group.

in both the routine and manual occupation groups. The shifts in the educational composition of the occupation groups imply that the quality of human capital has likely undergone substantial changes since 1970, highlighting the importance of accounting for these changes in price estimation.

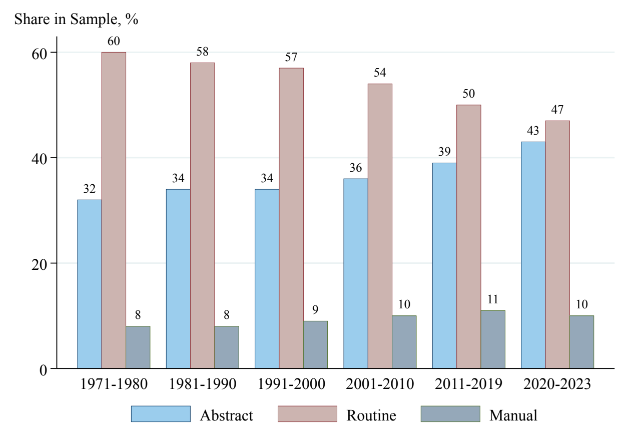
Figure 3 shows the evolution of log median hourly wages for workers in abstract, routine, and manual occupation groups. The trends in the log median wage reflect the expansion of wage inequality in the upper part of the wage distribution, and the compression of inequality in the lower part of the wage distribution explored in the RBTC literature. The log median hourly wage has increased for workers in the abstract group and decreased for manual and routine groups. These patterns generate an increase in the wage premium of abstract group workers relative to the routine group and manual group workers. The routine group has shown a stronger decrease in the median log wage than the manual group. Therefore, the wage premium of routine group workers relative to the manual group workers has declined.

Figure 1: Sample Composition by Decade

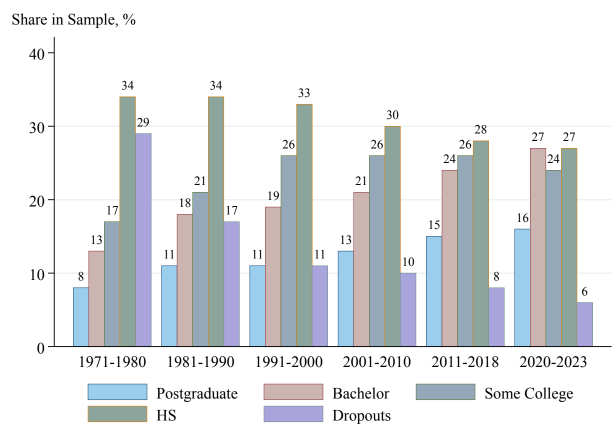
(a) Age



(b) Occupation

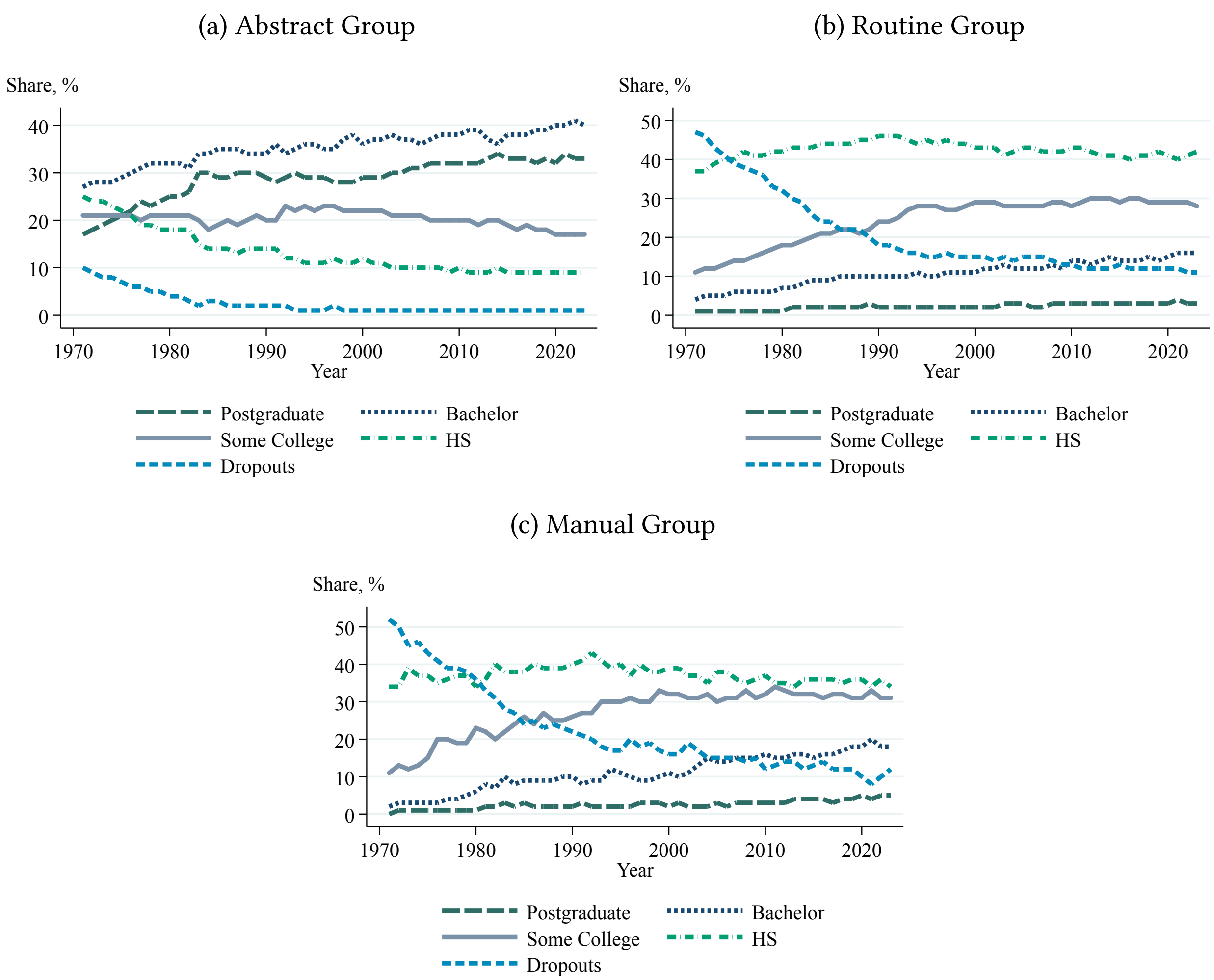


(c) Education



Notes: This figure displays summary characteristics for the sample of full-time full-year wage and salary male workers aged 30-64 in the MCPS 1971-2023. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked. Panel a) summarizes the age composition of the sample. Panel b) summarizes the occupational composition of the sample. Panel c) summarizes the educational composition of the sample.

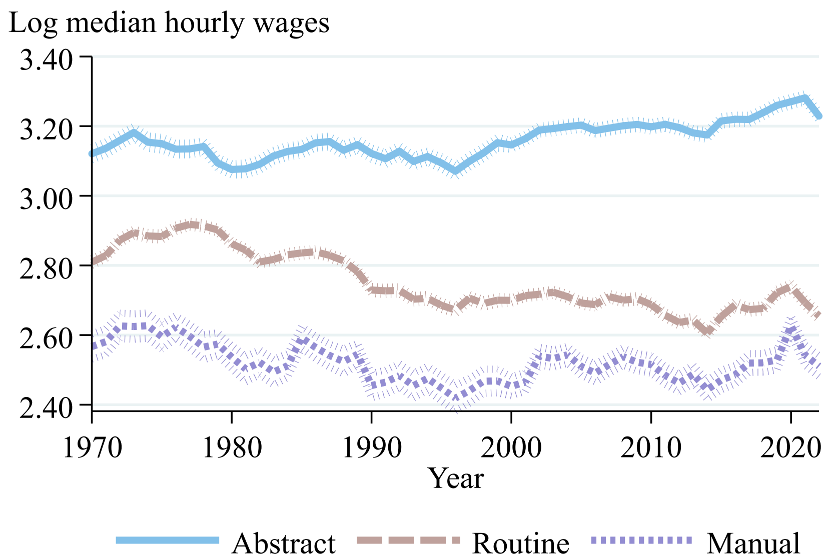
Figure 2: Educational Composition by Occupation Group



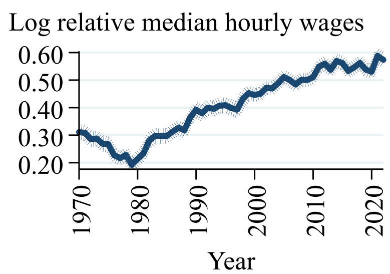
Notes: This figure summarizes the evolution of the educational composition of workers in abstract, routine, and manual occupational groups in the sample of full-time full-year wage and salary male workers aged 30-64 in MCPS. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked.

Figure 3: The Evolution of Log Median Hourly Wage

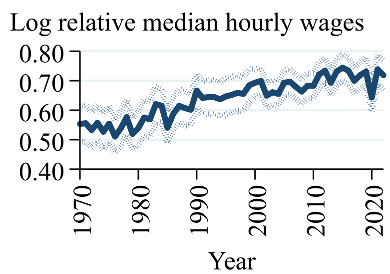
(a) All occupation groups



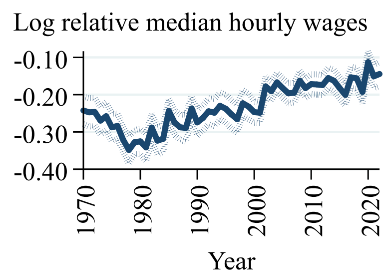
(b) Abstract vs Routine



(c) Abstract vs Manual



(d) Manual vs Routine



Notes: Panel a) displays the evolution of log median hourly wages in abstract, routine, and manual occupational groups for the sample of full-time full-year wage and salary male workers aged 30-64 in the MCPS. Panels b), c), and d) display the evolution of relative wages. All figures display 95% confidence intervals for the estimated log median hourly wages.

2.3 Flat Spot Price Identification and Occupational Human Capital

Applying the flat spot price identification method to occupational human capital requires identifying the flat spot age range for occupational groups and verifying that the occupational switching for workers in the flat spot age range is limited. If the flat spot age range is set too early, the price estimates are biased upwards as human capital accumulation by workers increases the wage. In contrast, if the flat spot age is set too late, the price estimates are biased downwards due to the impact of human capital depreciation on wage growth. If occupational switching is common for older workers, the wage effects from shifting occupational composition within a given cohort are attributed to the price change.

In order to identify the flat spot region, I exploit differences across occupation groups in educational attainment. Workers belonging to different education groups have different ages of entry in the labour market. This allows me to shift the flat spot region depending on the expected labour market entry age. For manual and routine groups, the average level of schooling over 1971-2018 slightly exceeds 12 years. Moreover, as shown in Figure 2, both occupation groups have high shares of high school graduates. Therefore the flat spot age range is set to be 46-55 for both groups, following the flat spot in Bowlus and Robinson (2012) for high school graduates.[15]

To set the flat spot age range for the abstract occupation skill group, I follow Bowlus and Robinson (2012) and exploit the prediction that if the share of the highest skill group contracts for consecutive cohorts of workers, the cohort effect for the average human capital stock is positive due to the positive ability selection effect and potential improvement in the human capital production technology. In this case, a cross-sectional change in wages for workers with positive cohort effects in their flat spot age range is lower than the change in human capital, and the peak in human capital profile occurs at later ages than the peak in earnings. My analysis reveals a flat spot region at 51-60.[16]

Finally, price identification requires that the occupational human capital stock is stable for workers in their flat spot age range. While occupational choice is endogenous and depends

[15] The length of the flat spot region is set to be 10 years to generate a reasonable sample size similar to Bowlus and Robinson (2012).

[16] Appendix C provides details on the analysis performed for the abstract occupational group.

on both the price and quantity of occupation-specific human capital for workers, I rely on a broad definition of occupational group encompassing multiple occupations intensive in abstract, routine, or manual tasks. I use the MORG files to analyze annual occupational switching patterns of full-time workers in the flat spot age ranges. More than 80% of workers in their flat spot age range remain in their occupational group, and this share is stable over the flat spot region. I further compare price series for a sample of full-time MORG workers with the sample restricted to occupation stayers and find that the effect of occupational switching on the estimated price series is limited.[17] Other studies have also shown that the role of selection into occupation stayers declines with age as match quality increases with experience.[18]

To estimate price series for the occupational human capital, I divide workers aged 30 to 64 into abstract, routine, and manual groups. Within each occupational group I estimate the median wage rates for workers in age/year cells for consecutive years using the quantile regression. The log price change between periods t and $t+1$ is estimated as the increase in log median wage between workers of age a in period t and workers of age $a+1$ in period $t+1$ averaged across all workers in the flat spot age range. I calculate the wage growth rate for a synthetic cohort of workers in period t as the change between log median wage of workers in year t averaged across all ages and the log median wage of workers in year $t-1$ averaged across all ages. The change in log efficiency units of human capital is computed as the difference between the change in log median wages and change in log prices of human capital.

3 Results

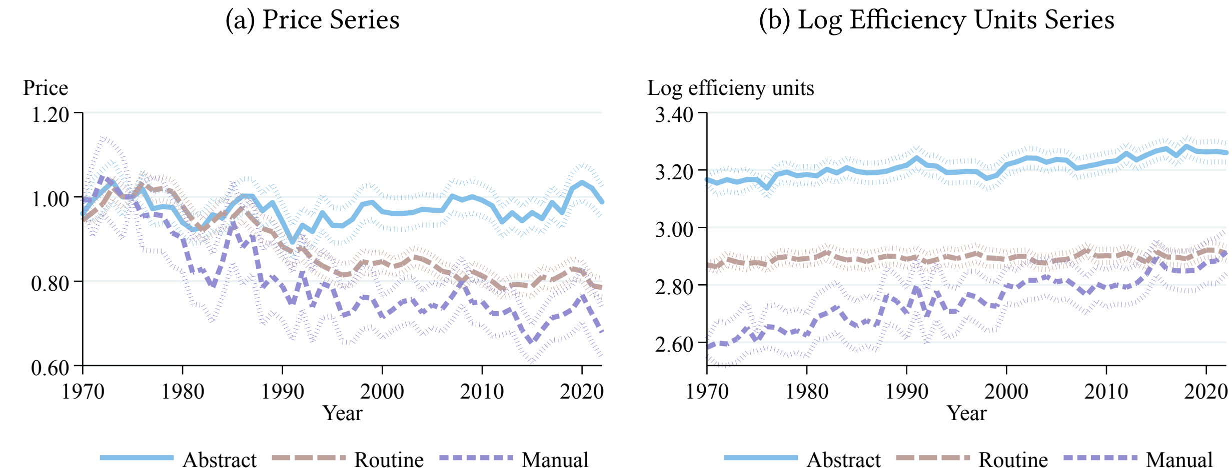
Figure 4 shows the estimation results for the prices and quantities of the occupational human capital stock in abstract, routine, and manual groups over 1970-2022. Figure 4a shows the estimated price series.[19] Although the price tends to fluctuate for all groups, price series for manual

[17] Appendix D provides details on the robustness of the price series to restricting the sample to occupation group stayers.

[18] Gathmann and Schönberg (2010) find that the frequency and the distance of occupational changes decline with age. Cavounidis and Lang (2020) show that, in a dynamic skill formation model, workers' response to wage shocks declines with age because of facing shortened horizon of future earnings and being more heavily invested in their existing stock of skills.

[19] Normalization of the price for one of the years is required. I normalized the prices in 1974 and 1975 to one due to the change in MCPS reporting of weekly hours worked.

Figure 4: The Evolution of the Price and Quantity of Occupational Human capital



Notes: This figure displays the evolution of estimated prices and quantities of human capital in abstract, routine, and manual occupational groups in the sample of full-time full-year wage and salary male workers in their flat spot age range in MCPS. The figure displays 95% confidence intervals for the estimated change in prices and log efficiency units of human capital between consecutive years.

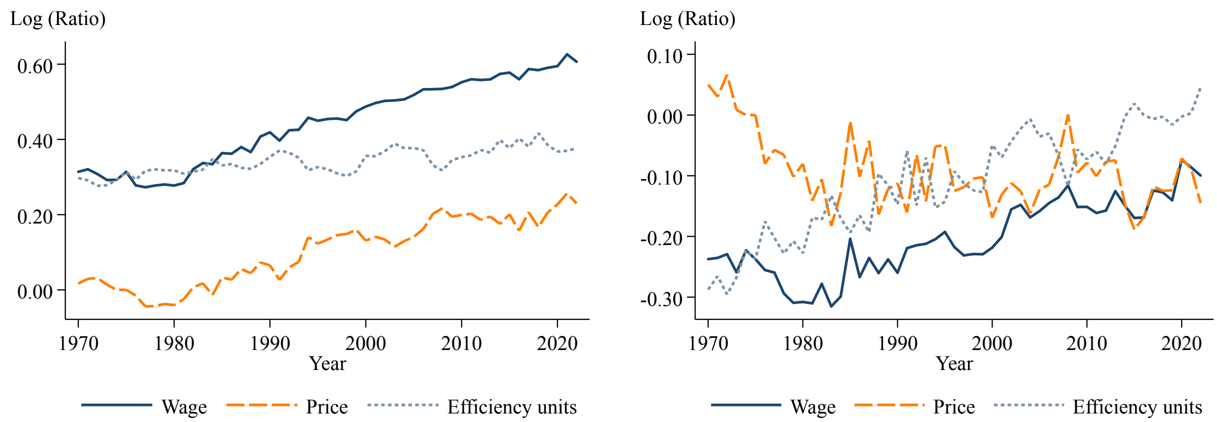
and routine groups decline over the observed period and are highly correlated while the price series for the abstract group remains relatively stable. Between 1970 and 2022, the prices for the routine and manual occupation group decline by more than 18% and 38%, respectively, while the price for the abstract group increases by 2.8%. The prices of human capital for all groups drop during the recessions of the mid-1970s, early 1980s, early 1990s, and COVID but the magnitudes of the declines and recoveries differ across groups.

The price of the abstract group relative to the routine group increases by 24.1 log points between 1980 and 2010. The increase in the price for the abstract group relative to manual and routine groups is consistent with both the SBTC and RBTC explanations of the growing inequality in the upper tail of the wage distribution. Using data from NLSY79 and NLSY97, Böhm (2020) quantifies the price increase per unit of occupational human capital in the abstract group relative to the routine group to be 25 log points between 1984-1992 and 2007-2009. Cortes (2016) uses the data from the Panel Study of Income Dynamics (PSID) to estimate a comparable 25 log points increase in the price of the abstract group human capital relative to the manual group human capital between 1976 and the mid-2000s.

In contrast, the high correlation between the price of the manual and routine groups pro-

Figure 5: Decomposition of Wage Premium

(a) Abstract Relative to Routine (b) Manual Relative to Routine



Notes: This figure displays the evolution of estimated log relative prices, log relative hourly wages and log relative efficiency units of human capital in abstract and manual groups relative to routine occupational group. The sample includes full-time full-year wage and salary male workers aged 30-64 in MCPS for the log relative hourly wages and log relative efficiency units of human capital series. The sample includes full-time full-year wage and salary male workers in their flat spot age range in MCPS for the log relative price series. See Appendix A.1 for 95% confidence intervals for the estimated changes between consecutive years.

vides less support for the predictions of RBTC, which implies a substantial increase in the price for the manual group relative to the price for the routine group. I estimate a small 0.3 log points increase in the price of the manual group relative to the routine group between 1980 and 2010. This finding contrasts with a significant increase in the price of the manual group relative to the routine group documented by Böhm (2020) and Cortes (2016) who estimate that the relative price increased by 32.9 log points between 1984-1992 and 2007-2009 and by 17 log points between 1976 and the mid-2000s, respectively.

Figure 4b shows the evolution of log efficiency units of occupational human capital. The human capital stock of the routine group is stable. The human capital stock of the abstract group slightly increases, with the human capital gap between the abstract and routine group not changing substantially. In contrast, the manual occupational group accumulates human capital stock at a high rate, which may be related to the change in educational composition in Figure 2. Under the assumption of stable human capital distributions in the population, the wage growth generated by this change would be attributed to a growing relative price of manual tasks.

Figure 5 decomposes the growth of the log median wage premium of abstract and manual occupations relative to routine occupations into the change in relative prices and the change in relative log quantities of human capital.[20] Since the 1990s, the growth in the wage premium of the abstract group relative to the routine group is generated by an increase in relative prices, which lends support to the SBTC theory and rising relative demand for abstract tasks. By contrast, the relative wage growth of the manual group compared to the routine group is driven by manual group workers accumulating human capital and catching up to the routine group's human capital stock levels.

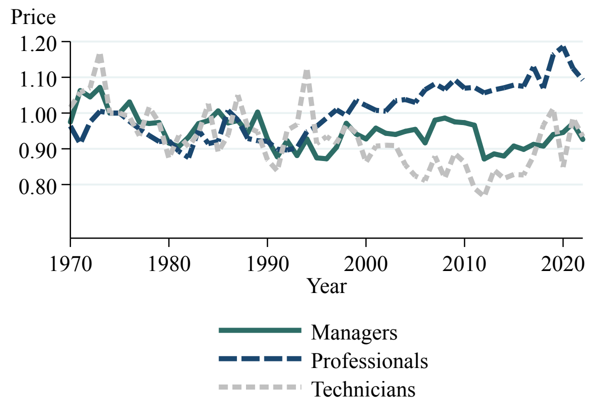
A possible explanation of the quality improvements observed for the manual occupational group is related to the shift of educational composition towards more educated workers. I find that the composition effects of the increasing educational attainment are positive and strong for all occupation groups. However, while the average level of schooling has increased in both the manual and the routine occupational groups, this increase has led to a higher growth in the manual occupational human capital stock than in the routine occupational human capital stock. Within the manual group, the log of the ratio of median hourly earnings of college graduates to high school graduates has increased by 47 log points between 1970 and 2018, compared to only 13 log points growth for the routine occupational group. A stronger increase in the college wage gap within the manual group indicates that later cohorts of high-skill workers in the manual group were more successful in accumulating the occupational human capital than high-skill workers in the routine group.

To find further evidence of changes to the relative demand for high-skill groups, I compare the trends in the price of abstract occupational subgroups. These subgroups incorporate workers in managerial occupations, professional occupations and technicians.[21] Between the subgroups, the professional occupation subgroup has the highest average levels of schooling and is dominated by workers with postgraduate degrees (see Appendix I). These high levels of training as measured by schooling required for the professional subgroup imply that it may be considered

[20] Appendix A.1 provides these estimates along with the 95% confidence intervals.

[21] Examples of occupations included in these subgroups are accountants, auditors, financial managers, and HR specialists for the managerial subgroup. The professional subgroup includes, for example, architects, scientists, doctors, and instructors. Finally, the technician subgroup represents occupations like dental hygienists, legal assistants and paralegals.

Figure 6: Price Series within the Abstract Group



Notes: This figure displays the evolution of estimated prices of human capital in professional, managerial, and technician subgroups of the abstract group. The sample includes full-time full-year wage and salary male workers in abstract occupational group aged 51-60 in MCPS. See Appendix A.2 for 95% confidence intervals for the estimated changes between consecutive years.

the group with the highest skill level across the abstract subgroups.

Figure 6 shows that even within the abstract occupation group, workers with the highest levels of skill disproportionately benefit from the growing demand for high-skill labour. Workers in professional subgroups have experienced the highest increase in the relative price of human capital followed by workers in managerial occupations.[22] Between 1970 and 2022, the price of professional workers with the highest average levels of schooling in abstract occupations increased by 8%, while the prices for managerial and technical occupations slightly declined. However, these changes are not statistically significant due to the small sample size in more detailed occupational subgroups. This implies that the increase in the wage premium of high-skill workers documented in the literature comes from an increase in the relative price, which corroborates the presence of SBTC. Moreover, the price was increasing at a stable rate. While Beaudry, Green, and Sand (2014) and Beaudry, Green, and Sand (2016) predict that after 2000 technological growth reached the maturity era, undermining the growth in the relative demand for abstract tasks, my results imply that the effects of SBTC did not disappear in the early 2000s.

[22]Appendix A.2 provides these estimates with 95% confidence intervals.

4 Conclusion

In this paper, I reexamine the RBTC explanation of the growing wage gaps between high-skill, middle-skill, and low-skill workers by allowing for the across cohort changes in the distribution of human capital. I estimate the evolution of the prices and quantities for abstract, routine, and manual occupational human capital applying the flat spot price identification method developed in Heckman et al. (1998) and Bowlus and Robinson (2012) on the MCPS data from 1970 to 2023.

My results indicate that wage gaps between the three occupational groups are driven by different forces. The relative price of the abstract occupational group has increased relative to both routine and manual groups, supporting theories relating the growing inequality to the technological growth stimulating the demand for high-skilled workers. The growth of the wage of the manual group relative to the routine group emphasized in job polarization literature is driven by the growth in relative quantities of human capital, not increases in relative prices. These findings together are consistent with the skill-biased technical change explanation of the growing inequality.

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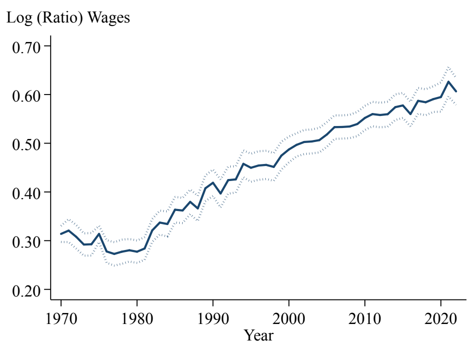
A Confidence intervals

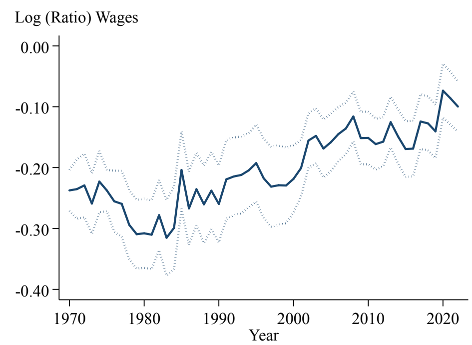
A.1 Decomposition of relative wage changes between abstract, routine, and manual groups

Figure A.1: Decomposition of Wage Premium: Log relative wages, prices, and efficiency units

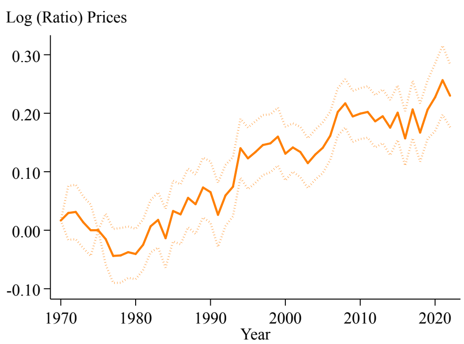
(a) Abs. vs Rout.: Wage



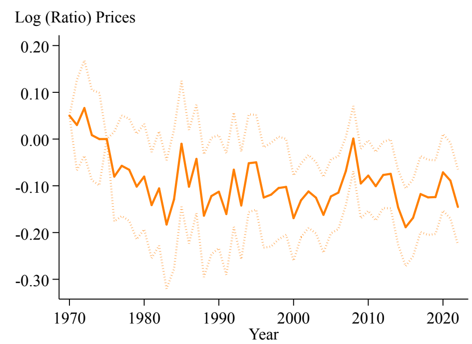
(b) Man. vs Rout.: Wage



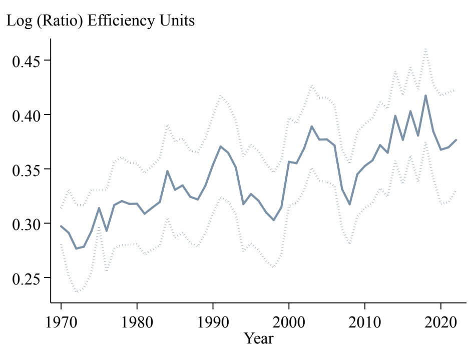
(c) Abs. vs Rout.: Price



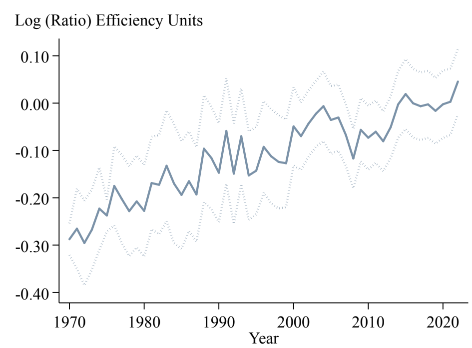
(d) Man. vs Rout.: Price



(e) Abs. vs Rout.: EU



(f) Man. vs Routine:EU

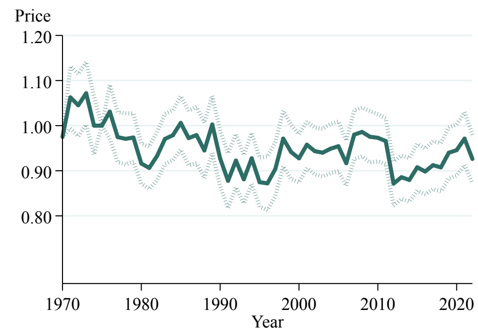


Notes: This figure displays the evolution of estimated log relative prices, log relative hourly wages and log relative efficiency units of human capital in abstract and manual groups relative to routine occupational group along with 95% confidence intervals for the estimated changes between consecutive years. The sample includes full-time full-year wage and salary male workers aged 30-64 in MCPS for the log relative hourly wages and log relative efficiency units of human capital series. The sample includes full-time full-year wage and salary male workers in their flat spot age range in MCPS for the log relative price series.

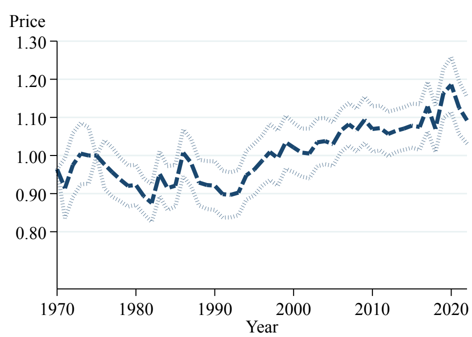
A.2 Prices within abstract group

Figure A.2: Prices within abstract group

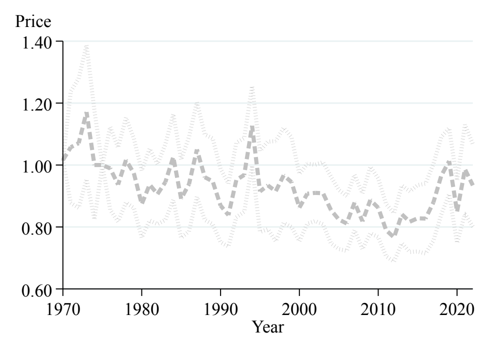
(a) Managerial



(b) Professional



(c) Technicians

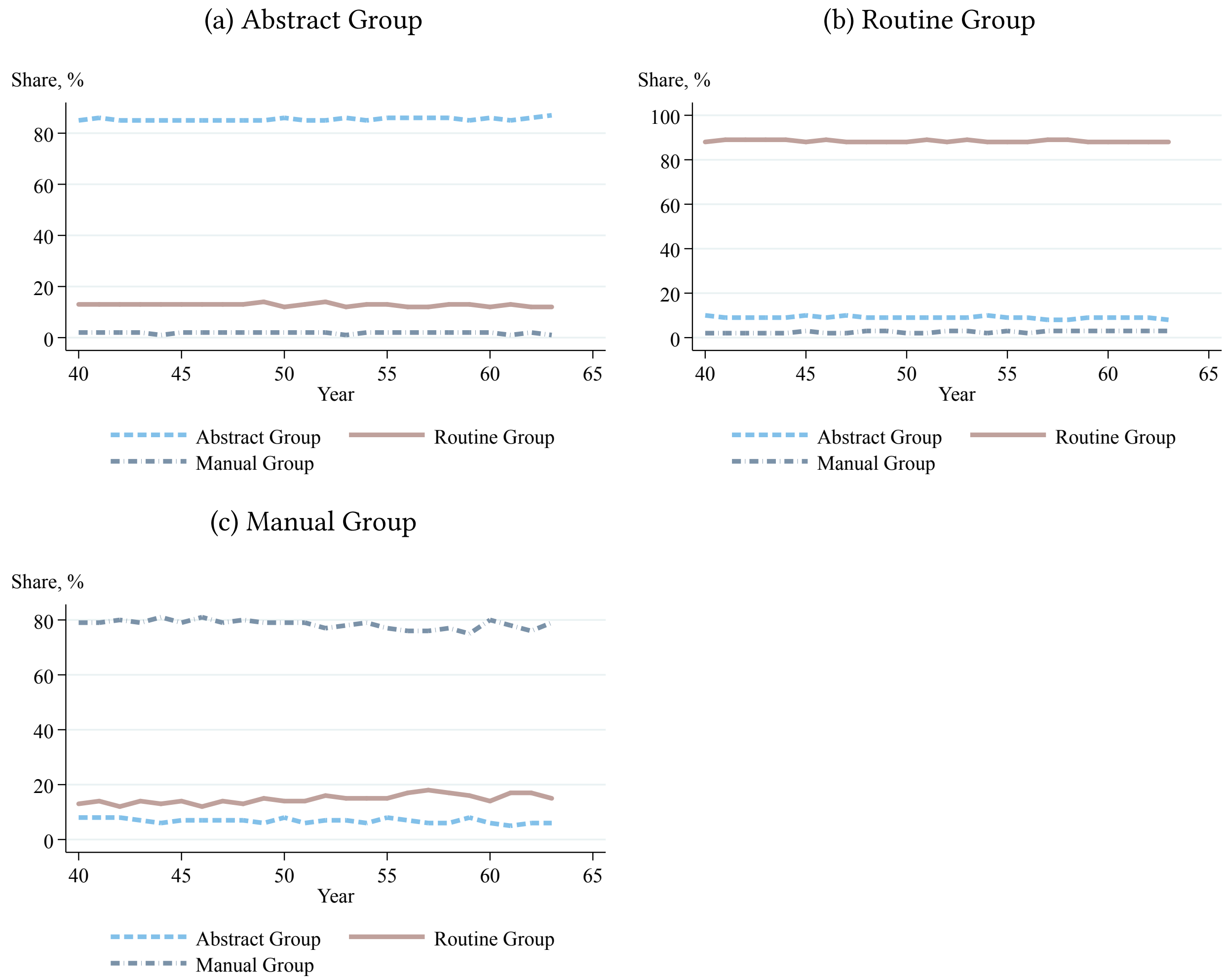


Notes: This figure displays the evolution of the estimated price series of human capital in managerial, professional, and technician subgroups of the abstract group along with 95% confidence intervals for the estimated changes between consecutive years. The sample includes full-time full-year wage and salary male workers aged 51-60 in the abstract occupational group in MCPS.

B Occupational Group Switching behaviour

If senior workers actively switch their occupational groups, the assumption that human capital stock is stable and homogeneous is unlikely to hold. I use the longitudinal component of the MORG data for 1982-2022 to analyze the role of occupational group switching behaviour in price estimation. The MORG samples consist of households who answer additional labour market questions in months four and eight in the Basic Current Population Survey. The responses in month four and month eight can be matched, providing information about changes in labour market outcomes over the year of participation in the survey. I restrict the MORG sample to full-time workers, defined as working 35-plus hours per week, who were employed as wage or salaried workers, have reported positive earnings and hours worked, and had a record of occupation in the fourth month of participating in the CPS. Self-employed and military workers are excluded from the sample. I find that the choice of the occupational group is persistent for senior workers. Figure

Figure B.1: Occupational Switching Patterns by Occupation Group



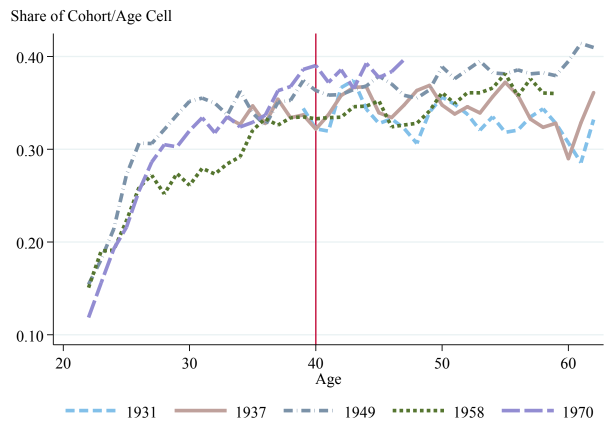
Notes: This figure displays the pattern of annual occupational switching behaviour between month-in-sample 4 and 8 of MORG. The sample includes full-time wage and salary male workers aged 30-64 in MORG 1982-2022.

B.1 demonstrates the pattern of occupation group switching for full-time workers employed in abstract, routine, and manual occupations in their month four in the sample. Over 80% of the abstract and routine group workers remain in their occupational groups over the year. Around

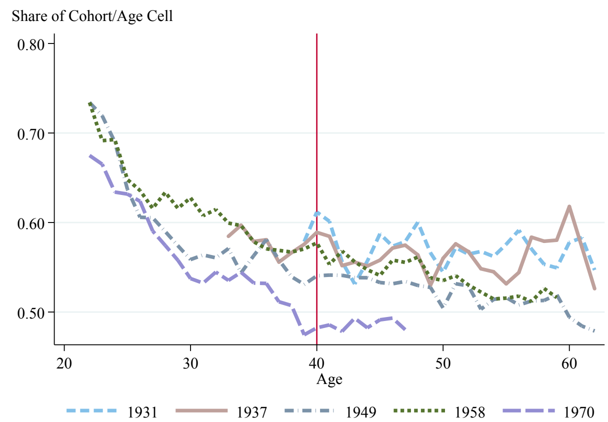
80% of workers in the manual group also persist in their choice of the occupational group.

Figure B.2: Occupational Group Sorting by Birth Cohort

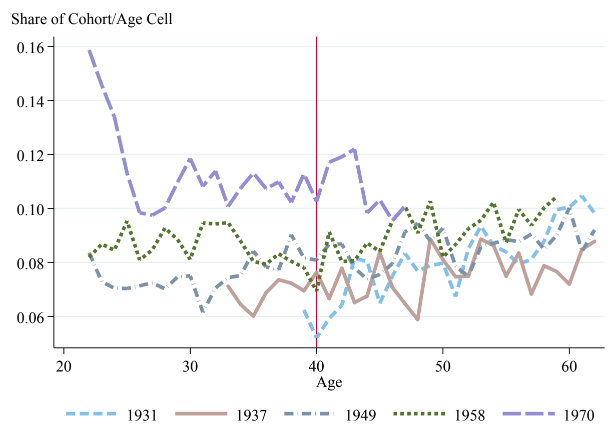
(a) Abstract Group



(b) Routine Group



(c) Manual Group

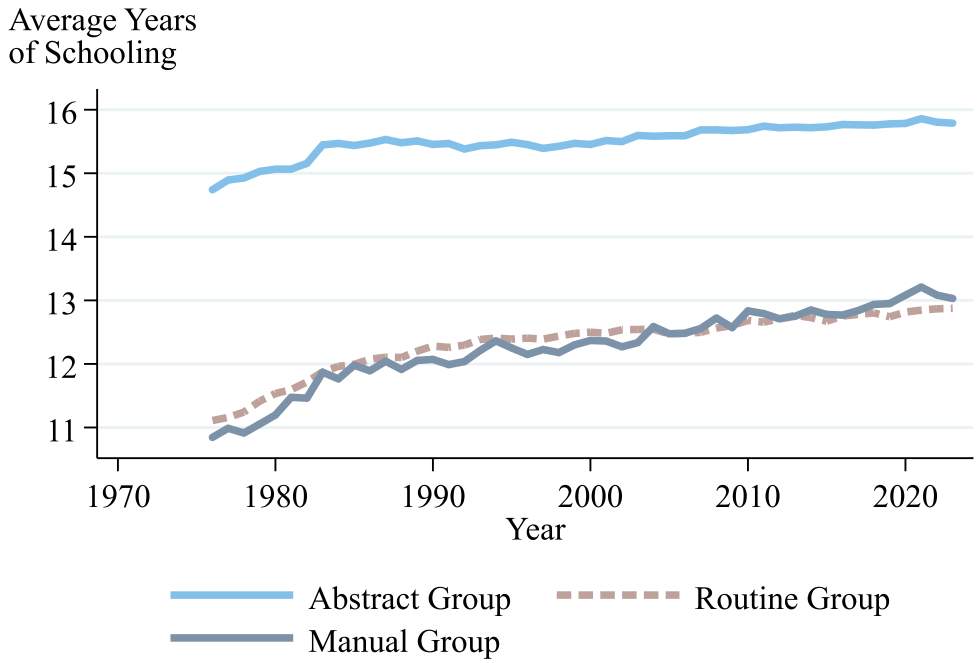


Notes: This figure summarizes the occupational composition of workers from various birth cohort by age for the sample of full-time full-year wage and salary male workers in the MCPS 1971-2023. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked.

Figure B.2 shows the life cycle occupational sorting of full-time, full-year workers in MCPS files for selected birth cohorts. Workers tend to begin their careers in routine or manual occupations and transfer to abstract occupations at later stages. Although the series tend to fluctuate due to the changes in the CPS sample, the occupational structure for all cohorts seems to become more stable by the age of 40. [23]

[23] The increase in the share of abstract group employment for workers in their 20s is also a result of the abstract group being on average more educated.

Figure C.1: The Growth of Average Schooling in Occupation Groups



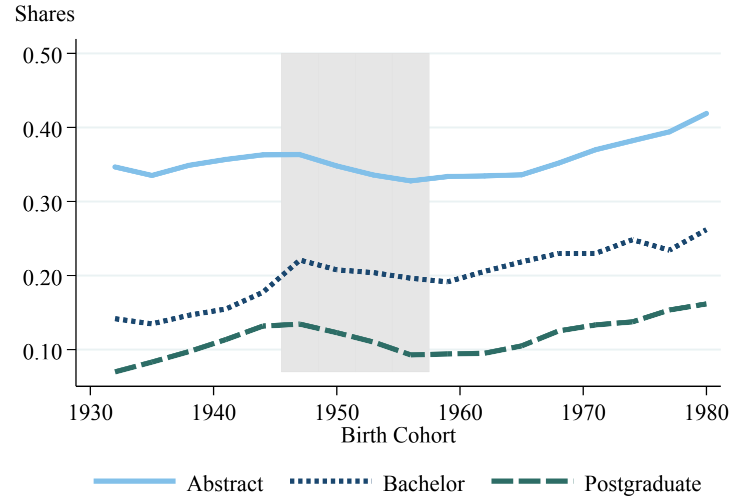
Notes: This figure summarizes the evolution of the average years of schooling by occupational group for the sample of full-time full-year wage and salary male workers aged 30-64 in the MCPS 1971-2023. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked.

C Flat Spot Identification

To set the flat spot for the occupational groups, I investigate their educational compositions. The educational composition of the routine group and the manual group is more diverse than that of the abstract group. High school graduates represent more than 40% of the routine group, and their share has been relatively stable over time. The share of high school graduates is also stable for the manual group, which has a higher share of high school dropouts and a higher share of workers with some college than the routine group. Workers with some college or even with a college degree have been increasingly substituting for high school dropouts in both routine and manual occupation groups.

Figure C.1 shows the evolution of the average level of schooling for workers in the occupation groups over the observed period. The average level of schooling has been steadily growing

Figure C.2: Share of Abstract Group Workers, Workers with Post-Graduate Degrees and a Bachelor Degree by Birth Cohort



Notes: This figure plots the share of FTFY workers between 35 and 40 years old in MCPS who are employed in abstract occupations, who have a bachelor's degree, and who have a postgraduate degree by birth cohort. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked.

for all occupation groups. The trend is parallel for occupation groups, with the abstract group exceeding the routine and manual groups by approximately three years of schooling. The average level of schooling over 1971-2018 slightly exceeds 12 years for both manual and routine groups. Therefore, the flat spot range is set to be 46-55 for both groups, similar to the flat spot range of high school graduates in Bowlus and Robinson (2012).

College graduates over the observed period have increasingly dominated the educational composition of the abstract group. Workers with at least some college education represented over 60% of the abstract group in 1971, and over 82% in 1983. In 2018 they represented approximately 90% of the abstract group. As the occupation group is dominated by workers who attended college, this group's flat spot age range should be similar to that of the college graduates.

To set the flat spot for the abstract occupational group, I apply the Bowlus and Robinson (2012) strategy to determine the potential flat spot range for the highest skill group of workers.

For a worker of age a belonging a synthetic birth cohort c in his flat spot range

$$\Delta lnS_a^c = lnS_a^c - lnS_{a-1}^c = 0.$$

In a given year, the price of an efficiency unit of human capital is fixed. Under the assumption that abstract workers of different ages supply homogeneous human capital, the difference between hourly wage rates of workers of different ages in the flat spot region represents a difference in their human capital stock up to a scale

$$lnw_a^c - lnw_{a-1}^{c+1} = lnS_a^c - lnS_{a-1}^{c+1}.$$

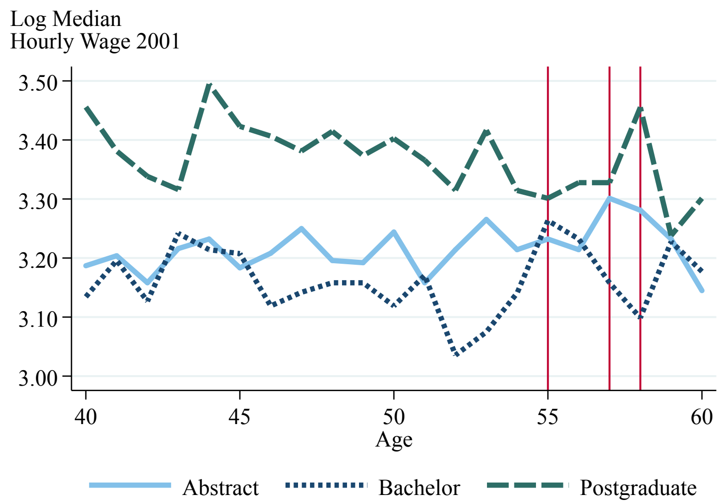
In the absence of cohort and compositional effects, it can be assumed that the average stock of human capital at age a for cohorts c and $c+1$ is the same, and the observed difference in the hourly wage rate between workers of consecutive cohorts will approximately identify the change in human capital:

$$lnw_a^c - lnw_{a-1}^{c+1} = \Delta lnS_a^c = \Delta lnS_a^{c+1}.$$

There are two potential sources of cohort effects for education groups: ability selection effects and the effects from changes in human capital production. If the initial ability distribution of the population is stable, the positive correlation between ability and selecting into the highest skill group implies that on the margin a worker who selects into the highest skill group has a lower ability than the average worker in this group and a higher ability than the average worker in lower skill groups. Therefore, the ability selection effect of the expansion of the highest skill group leads to a decline in both the average ability in this group and the average ability of lower skill groups. The effects from improvement in the human capital production function allow workers to accumulate the human capital stock at a higher rate conditional on their initial ability level, leading to an increase in the average human capital stock.

The abstract group is classified as a high-skill group in the task literature. It consists primarily of college-educated workers, while high school graduates dominate other occupation groups. Occupation switchers from routine and manual groups to the abstract group are more likely to transfer from the higher wage deciles in their occupation group to lower-wage deciles in the

Figure C.3: Log Median Hourly Wage Profile by Age in 2001



Notes: This figure plots the log median hourly wage of the abstract group, bachelor's degree, and postgraduate degree FTFY workers in MCPS 2001 by age. The sample excludes self-employed workers, workers without records of their occupation, annual earnings, or annual hours worked.

abstract group. The probability of switching to abstract jobs is increasing in workers' ability (Cortes, 2016). Therefore, a rising share of the abstract occupation group within a given birth cohort implies that more workers in this cohort are transferring from lower-skill occupation groups, introducing a negative selection bias.

Figure C.2 plots the share of FTFY workers between 35 and 40 years old in MCPS who are employed in the abstract group, who have a bachelor's degree, and who have a postgraduate degree. The share of workers in the abstract group follows a similar trajectory to workers' share with postgraduate and bachelor degrees. The share of abstract group workers in their late 30s is declining for cohorts born from 1947 to 1956. This change is likely to be driven by shifts in the population's educational composition rather than demand-driven changes in the labour market.

In 2001 the 1947 birth cohort reached 54, and the 1956 birth cohort reached 45. Since cohorts born between the 1947 and 1956 were characterized by a declining share of college graduates and declining abstract group employment, the ability selection effect is positive. As the average level of schooling has been increasing for the abstract occupation group over the observed period, it is likely to also benefit from the positive changes to the human capital production functions.

Thus, the aggregate cohort effect for abstract group workers between 1947 and 1956 should be positive. This means that in 2001, the wage growth observed for workers between these cohorts underestimates the life cycle human capital growth

$$lnw_a^c - lnw_{a-1}^{c+1} < \Delta lnS_a.$$

If the cohort effect for abstract group workers born between 1947 and 1956 is positive, the life cycle profile of earnings reaches its peak at an earlier age than for the human capital life cycle profiles. Figure C.3 plots the life cycle wage profile of the abstract group, bachelor's degree, and post-graduate degree workers in 2001. For workers with a bachelor's degree, the wage profile peaks at 55 years old. For workers with post-graduate degrees, the profile peaks three years later at 58 years old. The wage for workers in the abstract occupation group peaks at 57, reflecting the mixed educational composition of the group. For 57 years old workers, the cohort effect still makes the wage change lower than the change in human capital stock. Therefore, the abstract group's life cycle human capital profile cannot peak earlier than 57 years old.

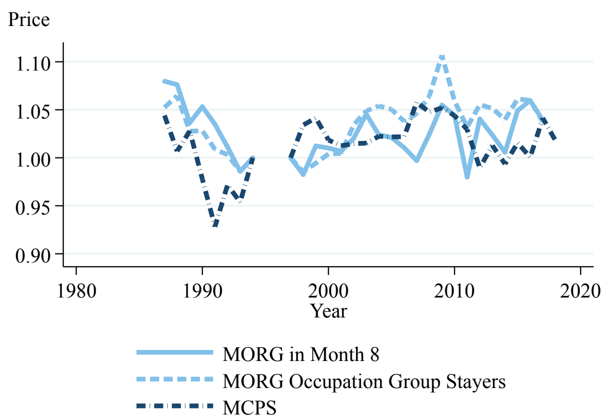
Based on the abstract group's educational composition and the cross-sectional evidence, the abstract group's flat spot range is selected to be 51-60 years old. It starts one year later than the flat spot region for workers with a four-year college degree in Bowlus and Robinson (2012). The sensitivity analysis performed in the following section shows that shifting the flat spot region for the abstract group to a later period to account for the increasing proportion of workers with postgraduate degrees has a modest effect on price estimates.

D Sensitivity of Price Estimation to Occupational Group Switching

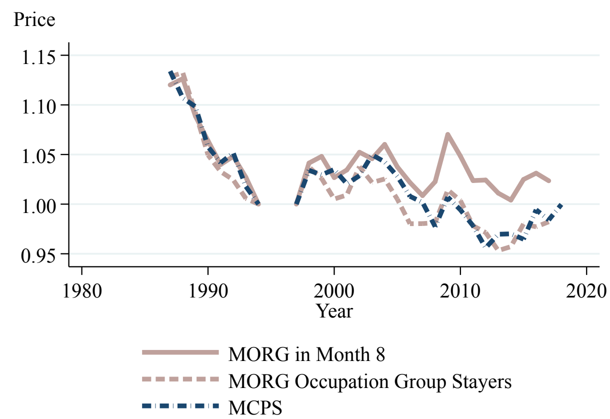
To see whether occupational switching behaviour can significantly alter the estimated price, I estimate the price series for occupational group stayers. Figure D.1 illustrates the benchmark price series estimated for the restricted and unrestricted samples. Unrestricted samples include full-time wage or salary workers in MORG during their month eight in the CPS and FTFY workers in the MCPS sample. The restricted sample includes full-time wage and salary workers in MORG who remained in the same occupational group over the year. Between 1984 and 1985, 1985 and 1986, 1994 and 1995, and 1995 and 1996 the CPS has changed numbering schemes for housing units, therefore matching of individuals is not performed across those years. I estimate the evolution of the occupational human capital price from 1987 to 1994 and from 1997 to 2017 when occupation stayers can be identified in the MORG sample.

Figure D.1: Sensitivity of Price Series to the Occupational Group Switching

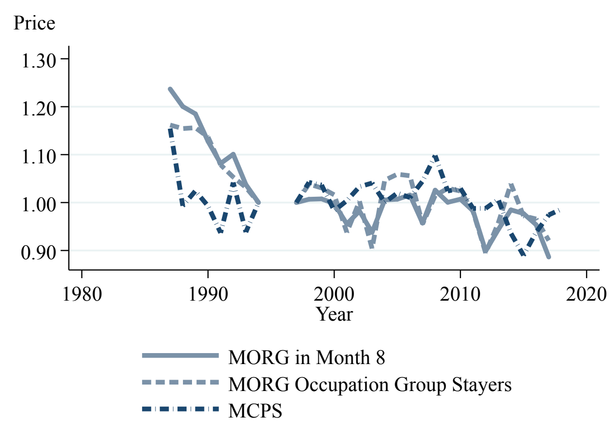
(a) Abstract Group



(b) Routine Group



(c) Manual Group



Notes: This figure plots the estimated baseline price series in MCPS along with the price series estimated for the sample of full-time workers in MORG based on wage data collected during month 8 in the sample, and the sample of full-time occupation stayers in MORG based on wage data collected during month 8 in the sample. The sample includes male wage and salary workers, excludes self-employed workers, workers without records of their occupation, earnings, or hours worked.

The price series for MORG occupational group stayers and the unrestricted MORG sample are highly correlated for all occupational groups, suggesting that the occupational switching behaviour has a limited effect on the price estimation results. Price series exhibit a price decline from 1987 to 1994 for all occupational groups and all samples, although the estimated decline in price is lower for the MCPS sample. Since the late 1990's prices in the routine and manual groups have been decreasing at a smaller rate than during the late 1980s and early 1990s, and prices for the abstract occupational group have been slowly increasing for all samples.

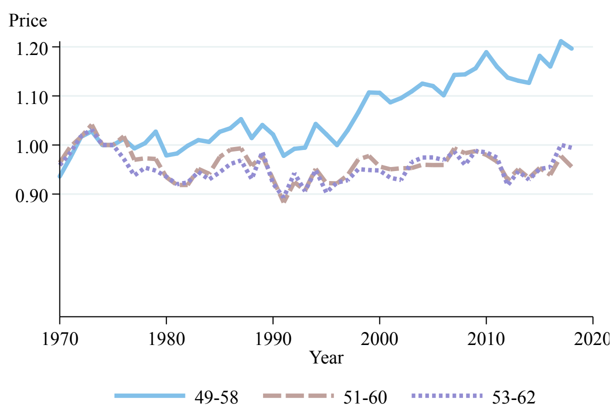
E Sensitivity to Changing the Flat Spot Age Range

This section analyzes the sensitivity of price series estimates to the choice of flat spot region. Figure E.1 demonstrates the sensitivity analysis for the price series estimated on the MCPS sample in abstract, routine, and manual groups, respectively. For the abstract group, setting the flat spot to begin at 51 years old or at 53 years old produces similar price series, while choosing an earlier flat spot seems to lead to the overestimation of the price. This is particularly true for the period after 1990 when the share of high school graduates and high school dropouts employed in the abstract occupation group reached a plateau in Figure 2. One explanation would be that around this period, the group became dominated by highly educated workers, who still experience the growth of human capital in their late 40's. If this is true, the median wage change would capture human capital accumulation and overestimate the price change. Setting the flat spot for later years to account for the increasing presence of workers with postgraduate degrees does not make price estimates substantially lower. This can be explained by low old age depreciation rates of cognitive skills.

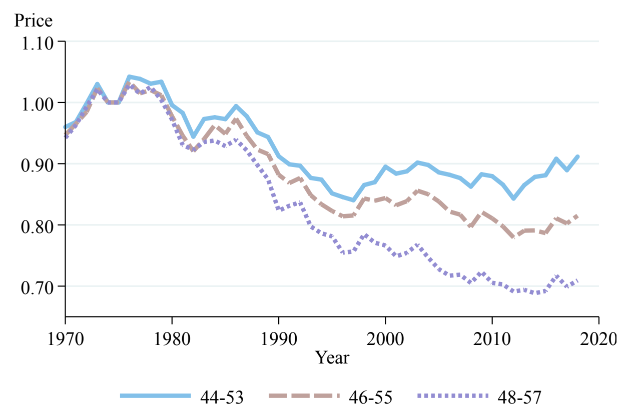
The price series for the routine group follow the expected pattern with early flat spots leading to the overestimation of the price series and late flat spots to underestimation as they potentially capture the effect of human capital depreciation and retirement. The manual occupation group price series are relatively insensitive to shifting the flat spot range. The price sequence generated by the 44-53 flat spot range lies below the price sequence generated by the 46-55 flat spot range for some years, but there are no persistent gaps between price estimates that are based on different flat spot ranges.

Figure E.1: Sensitivity of Price Series to Changing the Flat Spot Age Range

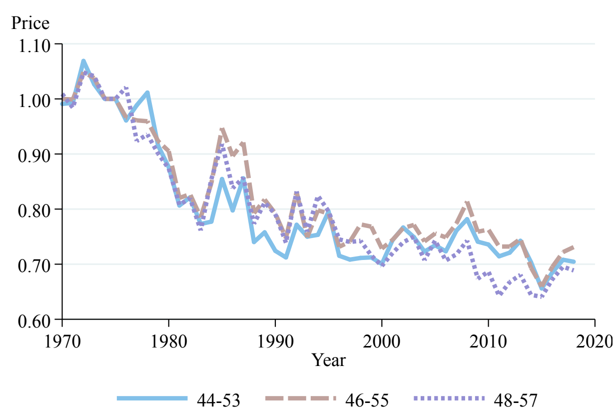
(a) Abstract Group



(b) Routine Group



(c) Manual Group



Notes: This figure displays the evolution of estimated prices of human capital for varying flat spot age ranges. The sample includes full-time full-year wage and salary male workers in their flat spot age ranges in MCPS.

F Wage Measure

The Bureau of labour Statistics (BLS) allocates missing values arising from the non-response using a hot-deck imputation method. Table 1 reports the proportion of allocated values in the estimation sample. The share of allocated values is substantial and exceeds 18% of observations for all groups.

Table 1: Sample size and proportion of allocated values for FTFY workers in their flat spot range

	Abstract Group [51-60 FTFY Male Workers]	Routine Group [46-55 FTFY Male Workers]	Manual Group [46-55 FTFY Male Workers]
Sample Size 1970-2017	95,559	181 353	30 054
Share of allocated values, % 1970-2017	19.5	18.6	19.3

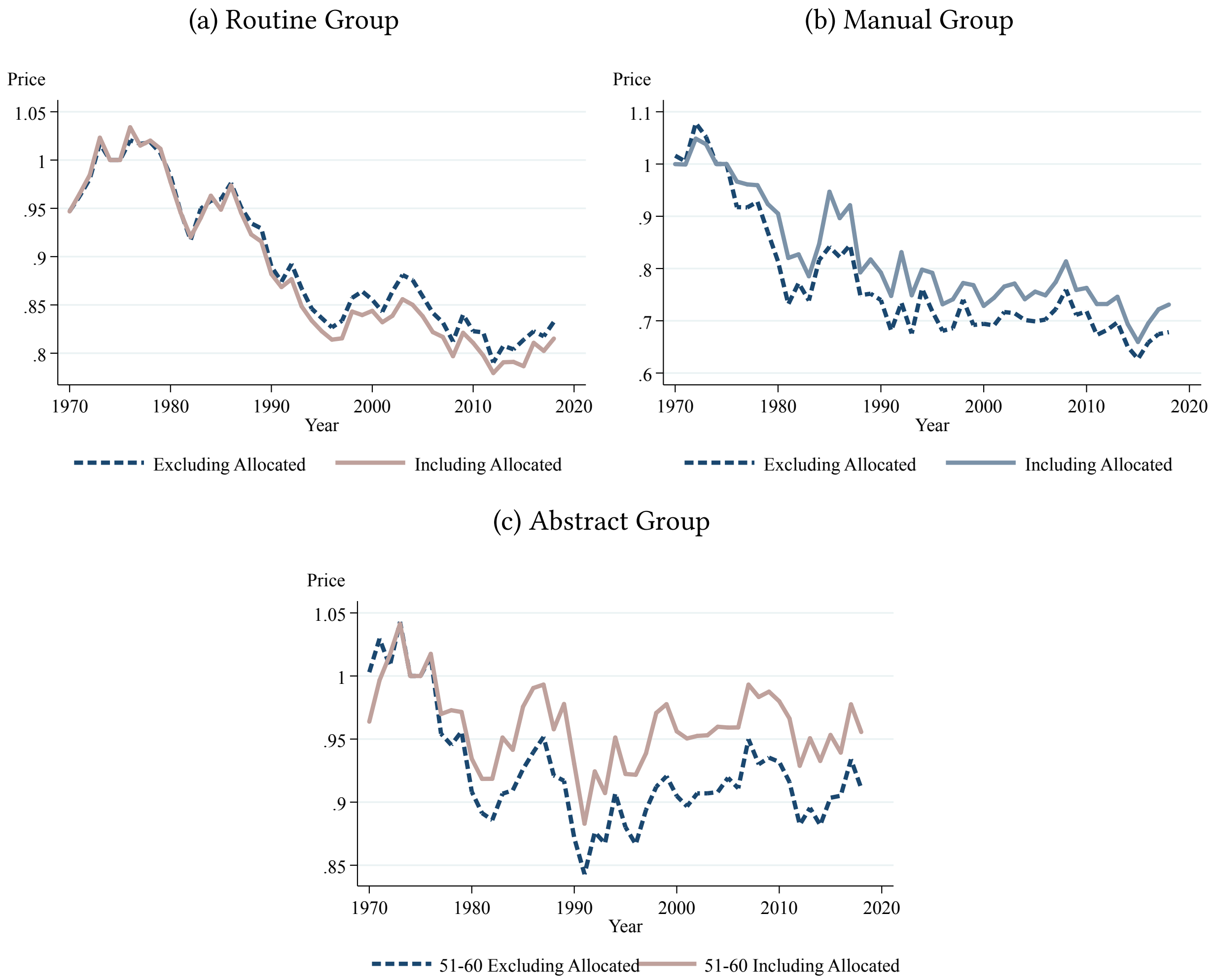
Figure F.1 compares the benchmark price series with the price series estimated after excluding the allocated values. Allocated values have a limited impact on the estimated price series of the manual and routine occupational groups. Excluding the allocated values from the estimation of the abstract group price generates a gap relative to the benchmark price series.

For the abstract occupational group excluding allocated values can lead to the underestimation of median wages. The earnings observations in the MCPS are missing in a non-random way, with older workers less likely to report their wage.[24] Figure F.2 analyses the patterns of wage allocation for the abstract group. Panel F.2a illustrates the share of allocated value for FTFY abstract group workers by age and decade of the data. The share of allocated values increases with the age. It is also particularly high for the 1990s and 2000s, reaching almost 30% of the sample for workers in their late 50's. Panel F.2b illustrates that for senior FTFY abstract group workers the BLS assigns wage values that are higher than the median wage for the sample that excludes allocated values, indicating that earnings are more likely to be missing for workers with higher earnings. Therefore, excluding allocated values from the price estimation will lead to the underestimation of the wage increase in the flat spot age range.

[24] Gottschalk et al. (2015) observe the same pattern in the MORG data.

Using the median hourly wages in the estimation allows me to solve the problem of inconsistently top-coded values in the CPS, however, it is common in the labour economics literature to perform the analysis using the average wage and average log wage measures. My findings are robust to the use of alternative wage measures. Figure F.3 compares the price series estimated using the median hourly wages, average hourly wages, and average log hourly wages. The increase in the price of the abstract group estimated with the use of average wages is even larger than the one reported for the benchmark price series. The estimated fall in the price of the routine group is lower for the average wages than for the median wages. However, the direction of the change is preserved.

Figure F.1: Sensitivity of Price Series to Allocated Values

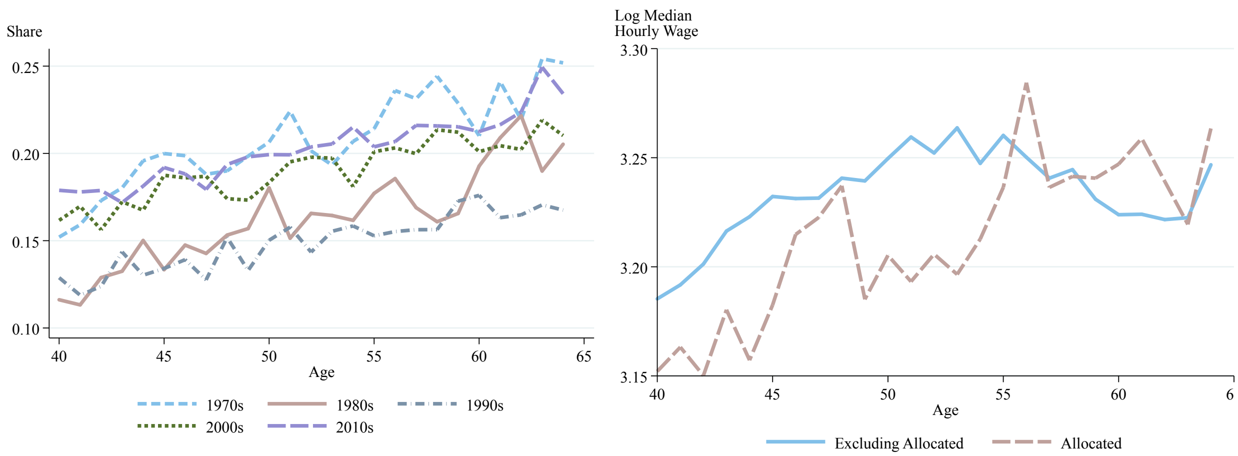


Notes: This figure displays the evolution of estimated prices of human capital while including and excluding allocated values. The sample includes full-time full-year wage and salary male workers in their flat spot age range in MCPS.

Figure F.2: Allocated Wages for Abstract Group

(a) The Share of Allocated Earnings Observations: Age and Decade

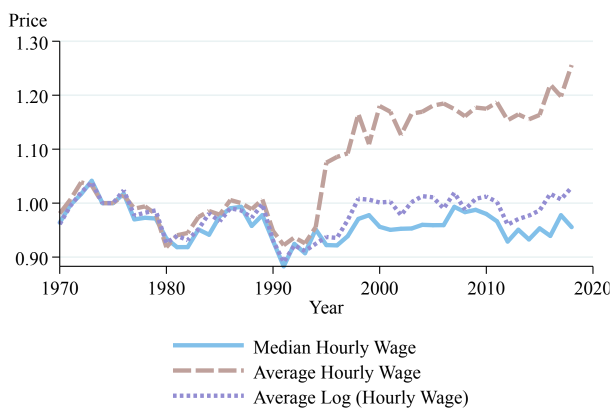
(b) Log Median Hourly Wage by Age Estimated for Allocated and Excluding the Allocated Earnings



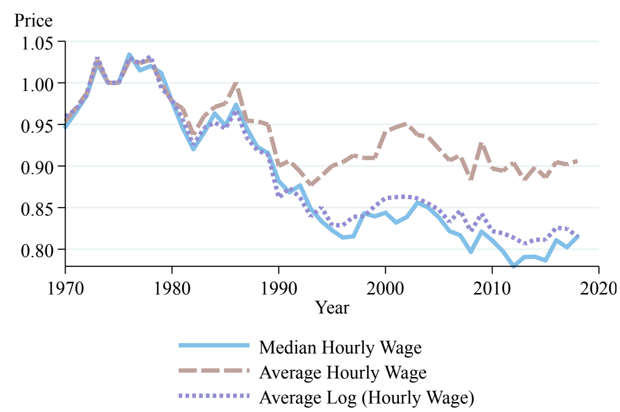
Notes: Panel (a) displays the average share of allocated earning values by age for various survey decades in the abstract group. Panel (b) displays the log median hourly wage by age estimated excluding allocated values and only for allocated values. The sample includes full-time full-year wage and salary male workers in the abstract occupational group in MCPS.

Figure F.3: Sensitivity of Price Series to Using Alternative Wage Measures

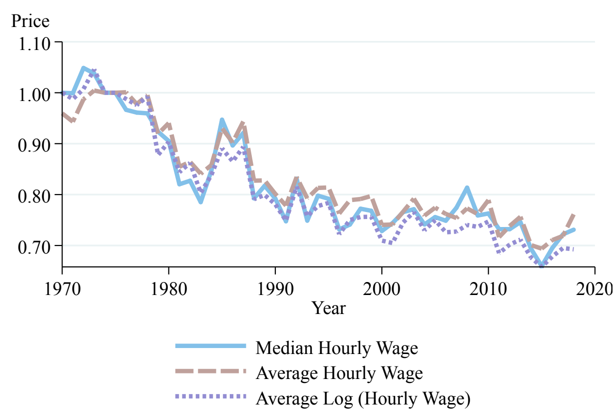
(a) Abstract Group



(b) Routine Group



(c) Manual Group



Notes: This figure displays the evolution of estimated prices of human capital using average wage, median wage, and log wage to compute the price series. The sample includes full-time full-year wage and salary male workers in their flat spot age range in MCPS.

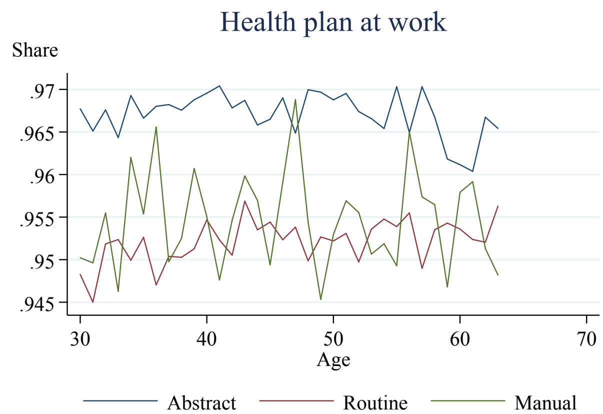
G Differences in contracts across occupational groups

MCPS asks respondents whether they have access to employer-provided health and pension plans. Figure G.4 summarized the life-cycle profile for the average share of workers who report having access to health plans or pension plans at work. Almost 95% of workers are covered by the employer's health plan, therefore, differences in compensation structure driven by healthcare plan coverage are likely to be small.

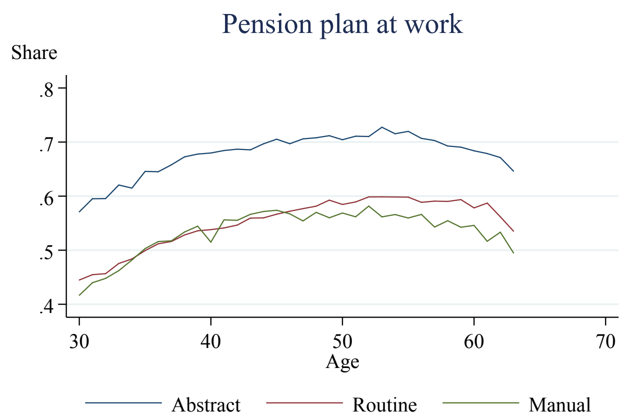
Abstract workers are more likely to have an employer-provided pension plan. It is possible that employers have to compensate workers in routine and manual groups for the lack of an employer-provided pension plan by offering higher wages for workers approaching retirement. In that case, the true decline in the price of manual and routine human capital can be even larger than what the estimated price series suggest.

Figure G.4: Share of workers with employer-provided pension and health plans by occupation group

(a) Health plan



(b) Pension plan



Notes: This figure summarized the average share of workers who report having access to health plans or pension plans at work by age. The sample includes full-time full-year wage and salary male workers in MCPS 1971-2023.

H Differences in job tasks across occupational groups

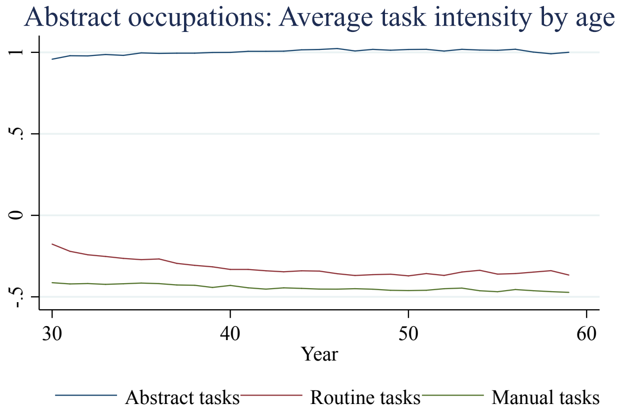
Following Acemoglu and Autor (2011) I sort workers into broadly defined occupational groups based on the Census classification of occupations. While commonly used in the literature (see, for example, Beaudry et al. (2016), Böhm (2020), Cavaglia and Etheridge (2020), and Cortes (2016)), it is possible that this grouping does not reflect worker's occupational tasks. This section shows that this occupational grouping preserves the relative ranking of occupational groups in terms of their task intensity.

To measure the average task intensity in occupational groups I use the crosswalk provided by Autor and Dorn (2013) to map the average of DOT 1977 task variables to worker's individual reported occupations. I follow Autor and Dorn (2013) and construct a measure of abstract task intensity as the average of "direction, control, and planning of activities" and "quantitative reasoning requirements". The measure of routine task intensity is the average of "adaptability to work requiring set limits, tolerances, or standards" and "finger dexterity". The measure of manual task intensity is "eye, hand, and foot coordination". I standardize all task intensity measures to be mean zero and the standard deviation equal to one.

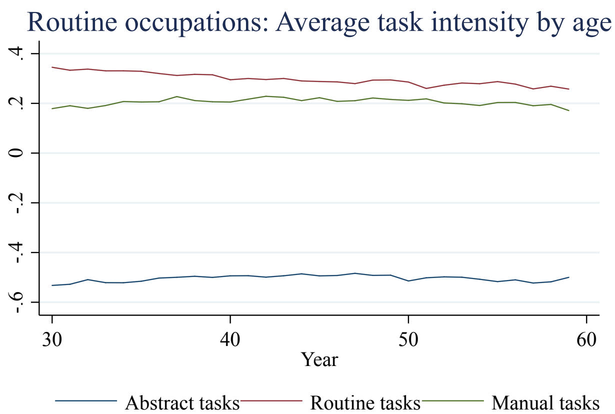
Figure H.5 shows the evolution of the average task intensity for all cohorts of workers by age. The average intensity of abstract tasks exceeds the average intensities of routine and manual tasks for workers in abstract occupational group. Moreover, the intensity of abstract tasks remains stable over the worker's age, implying that comparable occupational tasks, as measured at the occupation level, are assigned to workers of different age. The average intensity of routine tasks is the highest in the routine occupational group compared to other occupational groups. Routine tasks also have the highest intensity in the routine group compared to abstract and manual tasks. Finally, manual task intensity is the highest for the manual group. While the average intensity of manuals tasks exhibits a slight bell-curve shape, the average manual task intensity remains relatively stable for workers in their flat spot age.

Figure H.5: Average task intensity in occupation group by age

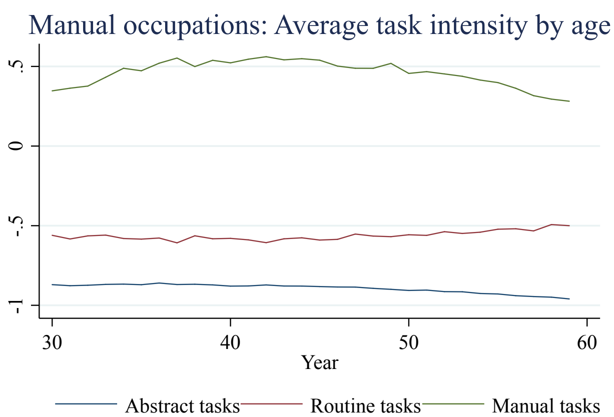
(a) Abstract group



(b) Routine group



(c) Manual group



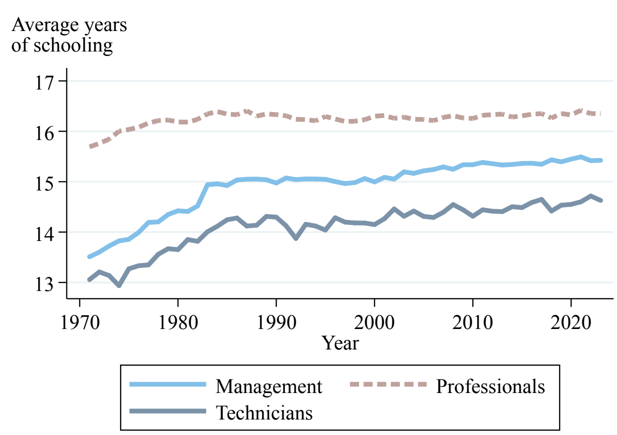
Notes: This figure summarized the life-cycle profile of the average intensity of abstract, routine, and manual tasks by broad occupational group. The tasks are computed using DOT 1977 task data provided in Autor and Dorn (2013). The sample includes full-time full-year wage and salary male workers in MCPS.

I Educational composition by abstract occupational subgroups

This section analyses the educational composition of occupational subgroups within the abstract group. These subgroups incorporate workers in managerial occupations, professional occupations and technicians.

Figure I.6 shows that workers in professional occupations, which include occupations like doctors, scientists, and instructors, were consistently more educated compared to workers in managerial and technical occupations. On average, there is at least a one-year schooling gap between professional and managerial workers. Figure I.7 explores the educational composition of these subgroups, and its evolution between 1970 and 2020. The professional occupational subgroup became dominated by workers with professional degrees beginning in the early 1970s, and the share of workers with postgraduate degrees has consistently exceeded 40%, compared to between 10% and 25% for the managerial group, and less than 20% for technicians. If training required to perform occupational tasks can be well approximated by schooling, this educational composition implies that professional occupations represent the highest skill levels.

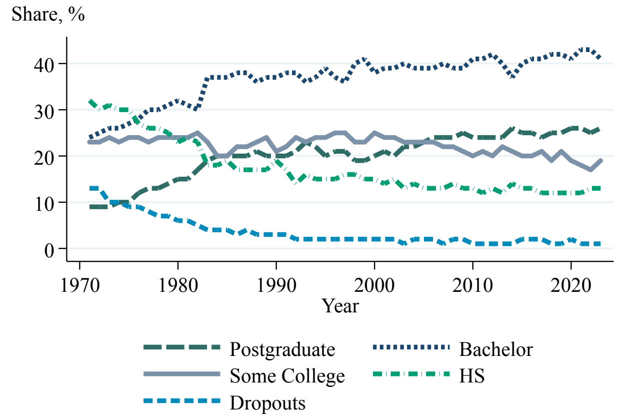
Figure I.6: Average schooling by abstract subgroups



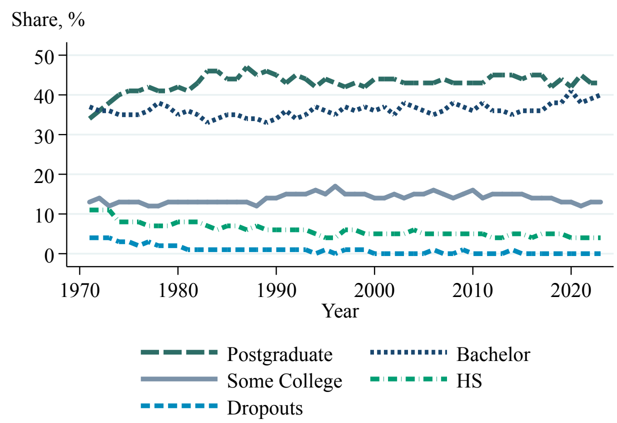
Notes: This figure summarized the average years of schooling within managerial, professional, and technician subgroups of the abstract group. The sample includes full-time full-year wage and salary male workers aged 30-64 in the abstract occupational group in MCPS 1971-2023.

Figure I.7: Educational composition within abstract subgroup

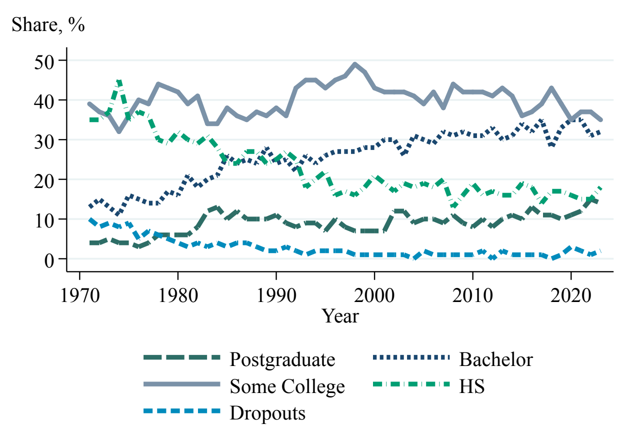
(a) Managerial



(b) Professional



(c) Technicians



Notes: This figure summarized the share of workers with various education levels within managerial, professional, and technician subgroups of the abstract group. The sample includes full-time full-year wage and salary male workers aged 30-64 in the abstract occupational group in MCPS.