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 roles of skill and routine-biased technical change in the rising U.S. wage inequality between 1970 and 2022. To quantify changes in prices and quantities of occupation-specific human capital, I use a *flat spot* price identification method that exploits the wage changes for workers approaching retirement to infer shifts in skill prices. Importantly, this method accommodates changes in cohort quality 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 in the 50 years I study. My results show that the price for the abstract group has increased relative to manual and routine groups. Conversely, the prices for manual and routine groups declined in absolute terms. This evidence supports the presence of skill-biased technical change (SBTC) increasing the relative price of high-skill human capital and is at odds with the implication of routine-biased technical change (RBTC) regarding the rising price of manual relative to routine human capital. Moreover, among abstract occupations, it is professional workers with higher levels of training who have disproportionately benefited from the changing relative demand for high-skill workers, compared to those in managerial and technician occupations, further supporting the presence of SBTC.

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1 Introduction

The changes of wage inequality in the U.S. over the last five decades have been characterized by diverging trends in the upper and lower tails of the wage distribution, with upper-tail inequality steadily rising and lower-tail inequality compressing (Acemoglu and Autor, 2011). These varying patterns became associated with changing wage differentials between workers employed in occupations that differ in their task content (Autor, Levy, and Murnane, 2003, Goos and Manning, 2007, Acemoglu and Autor, 2011). Wages have increased for workers in abstract-task occupations at the top of the wage distribution and manual-task occupations at the bottom, relative to those in routine-task occupations in the middle.

Understanding these trends in wage inequality is complicated because changing wage differentials can be driven by shifts in relative prices or by shifts in relative quantities of occupation-specific human capital, neither of which are directly observed by researchers. However, separately identifying changes in prices and quantities of efficiency units of human capital is important to understand the mechanisms behind the polarization of wages. Two leading explanations of wage inequality trends relate the observed changes in wages to the non-linear effects of technological growth on the relative prices of human capital. On the one hand, routine-biased technical change (RBTC), driven by innovations in technology and offshoring, drives the increase in prices for high-skill abstract and low-skill manual relative to the middle-skill routine occupational human capital (Autor, Levy, and Murnane, 2003, Acemoglu and Autor, 2011, Cortes, 2016, Böhm, 2020, Cavaglia and Etheridge, 2020). On the other hand, skill-biased technical change (SBTC) explains the rise in wage inequality by the increase in the relative prices for human capital of high-skill college-educated workers, predominantly employed in abstract occupations (Katz and Murphy, 1992, Autor, Katz, and Krueger, 1998, Carneiro and Lee, 2011).

The challenge of estimating prices and quantities of workers' occupation-specific human capital is compounded by shifts in the composition of workers employed in different occupations over the last half-century, as new cohorts entering the labour markets are more educated and potentially supply different human capital levels. As university enrollment expanded and the information technology revolution matured, college graduates "filtered-down" to lower-skill occupations compared to similarly credentialed workers entering the workforce in previous decades (Clemens, 2015, Beaudry, Green, and Sand, 2016). Changes in workers' human capital across cohorts extend beyond compositional effects, encompassing the emergence of new programs in universities and evolving methods of learning and teaching driven by technological advancements and social change.[1]

I reexamine the roles of routine-biased and skill-biased technical changes in explaining the growing wage inequality by allowing for across-cohort changes in the human capital distribution. I estimate the evolution of the price and quantity of human capital for abstract, routine, and manual occupational groups using data from the U.S. March Current Population Survey (MCPS). I find that, between 1970 and 2022, the price for routine and manual occupations declined by 18.6% and 38% respectively, while the price for abstract occupations increased by 2.8%. I show that, since the early 1990s, the growth in the relative wage premium for abstract workers compared to routine workers has been driven mainly by the growth in relative skill prices, corroborating the presence of SBTC as a driver of the increased relative demand for high-skill abstract workers. By contrast, the rising wage premium for manual workers relative to routine workers comes from the growth in the quantity of human capital in manual occupations, which is at odds with the predicted role of RBTC in driving the growing relative demand for manual occupations compared to routine occupations.

To estimate the price and quantity series, I adopt the flat spot identification approach developed in Heckman, Lochner, and Taber (1998) and Bowlus and Robinson (2012) 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 solely by skill price fluctuations (Ben-Porath,

[1] For example, Carneiro and Lee (2011) and Hendricks and Schoellman (2018) find that the college enrollment rate increase leads to significant 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. Moreover, they show that accounting for the role of cohort effects significantly changes the estimates of human capital prices for college and high-school graduates. Bastedo, Altbach, and Gumport (2016) highlight that the late 20th century witnessed a significant expansion of university curricula, driven by the growing influence of social movements and the differentiation of knowledge. Moreover, teaching and learning processes across established programs evolved in response to the information technology revolution.

1967). The key advantage of this price identification approach is that it allows for cohort effects in the production and distribution of human capital. I modify this method, which was originally developed for the education-based human capital, by identifying different flat spot age ranges for workers in each occupational group and verifying that the occupational switching within these age ranges is limited.

By inferring shifts in the prices of occupation-specific human capital from wage changes for workers in their flat spot age range, I am able to quantify how changes in both the prices and quantities of human capital contribute to evolving wage inequality over the last five decades. By focusing on workers' occupations rather than education I provide evidence that technological change affects workers differently depending on what they do in the workplace, even if they have similar education levels, extending the findings of Bowlus and Robinson (2012) for educational human capital and providing an explanation for the decrease in the human capital price for college-educated workers. Therefore, my results emphasize that the task content of jobs provides relevant information beyond workers' education and supports the use of task-based models to analyze changes in wage inequality.

While my estimates of changes in the relative prices of abstract human capital align with the previous literature, the estimates for manual human capital differ significantly.[2] These results highlight the importance of accounting for changes in the distribution of human capital over the five decades I study. An important difference between this paper and previous work on RBTC is that the latter often relies on the Roy model of selection into occupations, assuming no cohort effects in the population distribution of skills or in the relationship between workers' ability and their occupational human capital.[3] Under the assumption of a stable human capital distribution, wage growth driven by human capital would instead be attributed to price changes. This is evident in manual occupations, which, according to my findings, have experienced substantial growth in human capital over the last half-century.

[2]For example, I estimate a 24 log points increase in the price of abstract relative to the routine workers' human capital between 1980 and 2010 similar with the 25 log points increase between 1984-1992 and 2007-2009 estimated by Böhm (2020). By contrast, I find a small 0.3 log points increase in the price of the manual workers' relative to the routine workers' human capital between 1980 and 2010 once I account for cohort effects, while Cortes (2016) estimates that the relative price increased by 17 log points between 1976 and the mid-2000s.

[3]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 occupations relative to the routine occupations.

Further, I show that the increase in the price within the abstract occupations is driven disproportionately by workers with the highest skill levels. Between 1970 and 2022, the price for professional occupations, those with the highest average levels of schooling in abstract occupations, increased by 8%, while the prices for managerial and technical occupations slightly declined. Even though this difference is not statistically significant, due to a reduction in sample sizes, these findings suggest that the increase in the wage premium for high-skill workers documented in the previous literature was driven by an increase in the relative price of human capital of the most skilled workers in abstract occupations.[4] This result further corroborates that, over the last decades, technology increasingly benefited the productivity of high-skill workers at the top of the wage distribution.

This paper proceeds in four sections. Section 2 explains how the flat spot price identification methodology is 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 growing inequality. Section 4 concludes.

2 Data and Methodology

2.1 Data and Summary 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, that 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.[5]

[4] 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.

[5] 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

Following Bowlus and Robinson (2012), I construct an hourly wage measure by dividing inflation-adjusted annual earnings by annual labour supply.[6] 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 annual 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.[7]

I sort workers into abstract, routine, and manual occupational groups (Acemoglu and Autor, 2011). 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 literature (for example, Beaudry et al., 2016, Böhm, 2020, Cavaglia and Etheridge, 2020, Cortes, 2016).[8] 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.

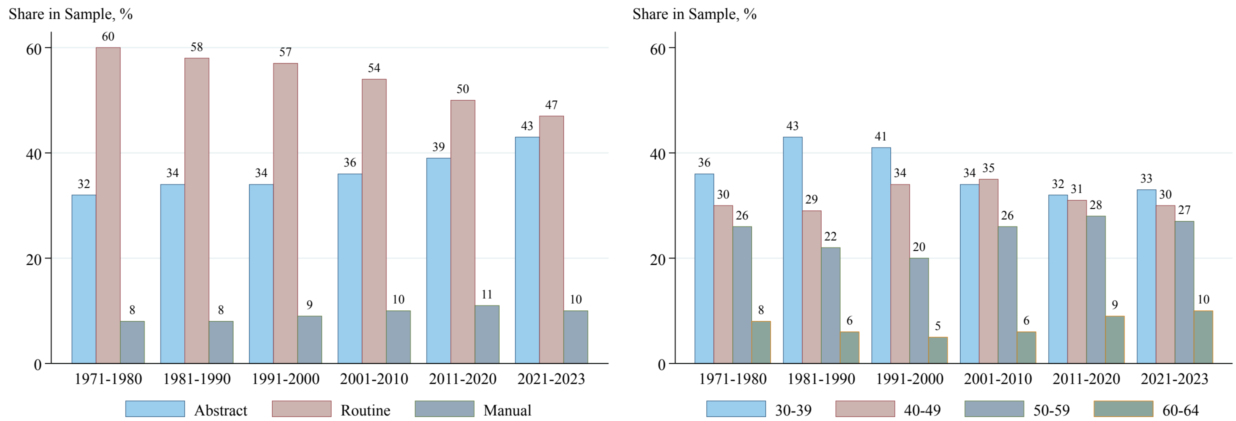
Figure 1 depicts the age and occupational composition of the sample. Panel 1a illustrates the polarization of the labor market's occupational structure, with an increasing share of abstract and manual occupations and a declining share of routine occupations. Despite this trend, workers in routine occupations remain the largest group in the sample, while those in manual occupations

earners who report their earnings as an annual amount, which limits the potential to select individuals with strong labour market attachment.

[6] 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.

[7] 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).

[8] In Appendix J I analyze the average task intensity across occupation groups based on the the Dictionary of Occupational Titles (D.O.T.) data. I show 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 the abstract occupational group.



(a) Occupation

(b) Age

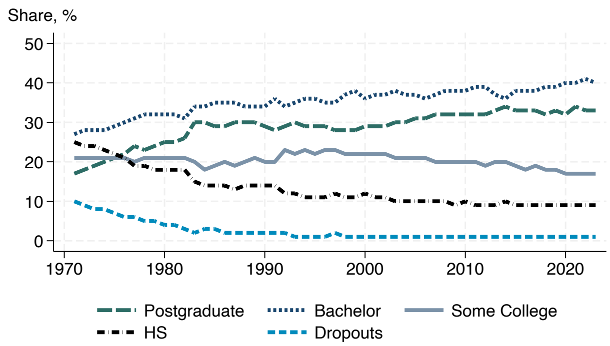
Figure 1: Sample Composition by Decade

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 occupational composition of the sample. Panel b) summarizes the age composition of the sample.

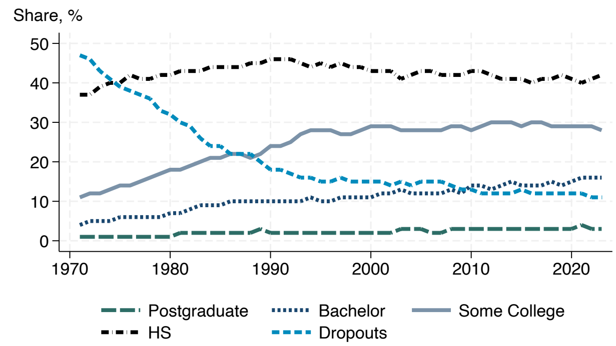
form the smallest. Panel 1b highlights an aging trend in the sample over time, consistent with U.S. demographic patterns. Over the decades, the share of workers in their 40s fluctuated between 29% and 35%, while workers in their 50s accounted for 20% to 28% of the sample.

Figure 2 illustrates the evolution of the educational composition of workers in abstract, routine, and manual occupations. Abstract occupations have been increasingly performed by the most educated group of workers, while less-educated workers have been crowded out of abstract occupations into manual and routine occupations. As a growing share of new labor market entrants has obtained college degrees, workers with some college education or bachelor's degrees have increasingly sorted into routine and manual occupations, reflected in a lower share of high school dropouts and graduates, whose presence in these occupations has declined. The shifts in the educational composition of occupations driven by the overall expansion of college education as well as the transformation of the university curriculum and learning imply that the distribution of human capital has undergone substantial changes since the 1970s (Bowlus and Robinson, 2012, Bastedo, Altbach, and Gumport, 2016). This underscores the importance of accounting for the role of cohort effects in price estimation.

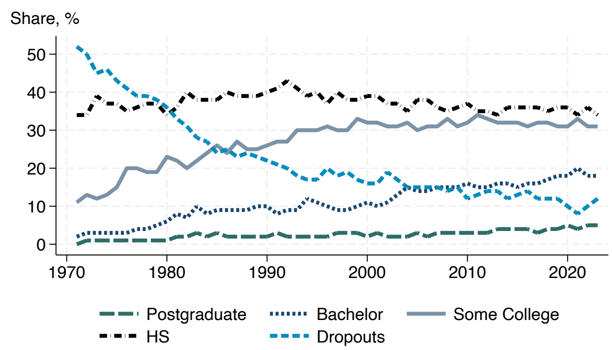
Figure 3 shows the evolution of log median hourly wages for workers in abstract, routine,



(a) Abstract Group



(b) Routine Group

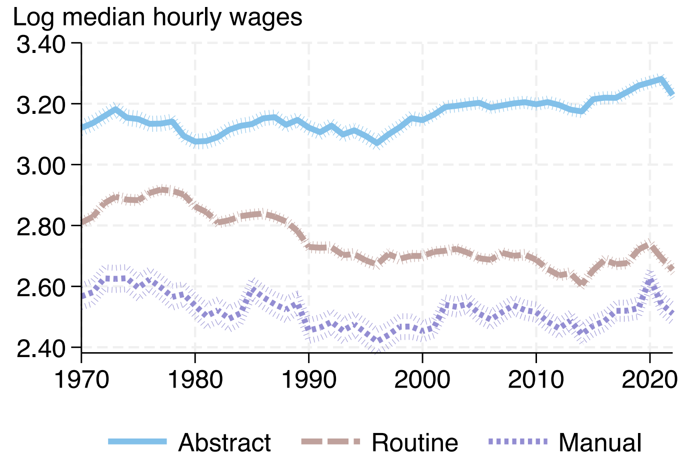


(c) Manual Group

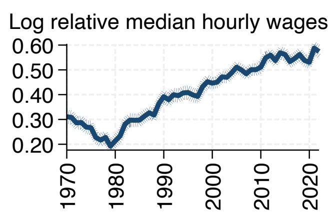
Figure 2: Educational Composition by Occupation Group

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.

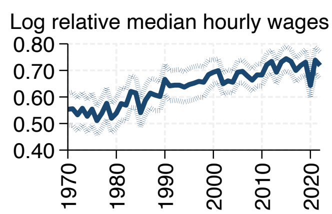
and manual occupations. The trends in the log median wage reflect the expansion of wage inequality in the upper part of the wage distribution, and the compression of inequality in the lower part of the wage distribution (Böhm, 2020, Acemoglu and Autor, 2011). The log median hourly wage has increased for abstract workers and decreased for manual and routine workers. These patterns generate an increase in the wage premium for abstract occupations relative to routine and manual occupations . Routine workers have shown a stronger decrease in the median log wage than manual workers. Therefore, the wage premium for routine occupations relative to manual occupations has declined.



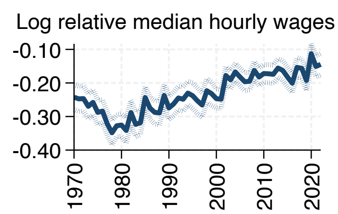
(a) All occupation groups



(b) Abstract vs Routine



(c) Abstract vs Manual



(d) Manual vs Routine

Figure 3: The Evolution of Log Median Hourly Wage

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.

2.2 Methodology

The hourly wage earned by a worker employed in a given occupation depends on the quantity of occupation-specific skill they possess and on how the market values this skill. Formally, the period t hourly wage for a worker i of age a is the product of their supplied level of efficiency units of human capital specific to their broad occupational group o specializing in abstract, routine, or manual tasks, $o = \{A,R,M\}$, $H^{o,a}_{i,t}$, and on the current efficiency unit price of occupational human capital P^o_t as follows

$$Wage^{o,a}_{i,t} = P^o_t \times H^{o,a}_{i,t}. \tag{1}$$

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 levels, neither of which are directly observed in the data. Moreover, different cohorts of workers are likely to differ in their human capital distribution due to dramatic shifts in the educational composition of workers across time and technological and methodological advancements in the education.[9] Nevertheless, it is important to separately identify the evolution of prices and quantities of human capital over time because they have different implications for the underlying causes of changing wage inequality.

I identify occupational human capital price sequences by applying the flat spot price identification method of Heckman, Lochner, and Taber (1998) and Bowlus and Robinson (2012). The method builds on the Ben-Porath (1967) human capital investment model, that 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 around which human capital levels are constant. Under this identification assumption, workers in their flat spot age range, a^*, have stable levels of human capital

$$E[lnH_{i,t}^{o,a^*} - lnH_{i,t-1}^{o,a^*-1}] = 0, \tag{2}$$

and the wage growth during the flat spot age range reflects changes in the price of human capital

$$E[lnW_{i,t}^{o,a^*} - lnW_{i,t-1}^{o,a^*-1}] = lnP_t^o - lnP_{t-1}^o. \tag{3}$$

I use this to identify the price change for an efficiency unit of human capital from the average wage growth of workers in the age range of the flat spot of their human capital profile.

To implement the flat spot method using the MCPS data, I estimate median hourly wages, human capital price and quantity series in each occupational group using quantile regressions. First, the log price change between periods t and $t + 1$ is estimated as the increase in log median

[9] Carneiro and Lee (2011) and Hendricks and Schoellman (2018) show that higher college enrollment rates significantly altered the average quality of college graduates' human capital. Bowlus and Robinson (2012) and Bastedo, Altbach, and Gumport (2016) highlight that production of human capital in universities has changed. Attanasio, Blundell, Conti, and Mason (2020) shows that even the distribution of human capital in early childhood has changed for cohorts born decades apart.

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. Second, the wage growth rate for a synthetic cohort of workers in period t is computed 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. Finally, the change in log efficiency units of human capital is computed as the difference between the change in log median wages and log prices of human capital.

Applying the flat spot price estimation method to occupational human capital requires identifying the flat spot age range for workers in each occupational group. 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. 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. In order to identify the flat spot region, I build on the relationship between labour market entry age and flat spot age range for workers with varying levels of education documented in Bowlus and Robinson (2012) and exploit the educational composition of workers and compositional shifts across cohorts to determine the flat spot age range.

To set the flat spot age range for manual and routine workers I exploit differences across occupations in educational attainment. The average level of schooling for workers in these occupations over 1971-2018 slightly exceeds 12 years (see Appendix E Figure E.1). Moreover, as shown in Figure 2, both manual and routine occupations 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.[10]

Abstract occupations are dominated by college-educated workers. Figure 2 shows that the share of workers with bachelor degrees in abstract occupations increased from 27% in 1971 to 40% in 2023. Moreover, workers with postgraduate degrees consistently found employment in abstract occupations, with their share among abstract workers nearly doubling over five decades, from 17% in 1971 to 33% in 2023. This implies that the flat spot age range for abstract workers falls between that of workers with bachelor's and postgraduate degrees. Sensitivity analysis confirms that my findings for abstract occupations are robust to shifting the flat spot age range from ages

[10] 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).

50 to 59, that of college graduates in Bowlus and Robinson (2012), to ages 53-62 (see Appendix G Figure G.1a).

Furthermore, to narrow down the flat spot age range for abstract occupations, I use the prediction from Bowlus and Robinson (2012) that if the share of the highest skill group contracts across consecutive cohorts, the cohort effect on average human capital level is positive due to ability selection and potential improvements in human capital production technology. When positive cohort effects are present, the cross-sectional wage difference between older and younger workers underestimates the actual increase in human capital with age. As a result, the cross-sectional earnings profile peaks at younger ages compared to the human capital profile, introducing a lower bound on the flat spot age range. For cohorts born between 1947 and 1956, the share of workers in abstract occupations in their late 30s, as well as the share of college graduates, decreased. Cross-sectional wage data from 2001, when the 1947 cohort was 54 and the 1956 cohort was 45, reveals that wages for abstract workers peaked at age 57. Thus, the human capital profile for abstract workers must peak later than 57, leading me to select 51–60 as the flat spot age range for my baseline results (see Appendix E).

2.3 Discussion of Methodology

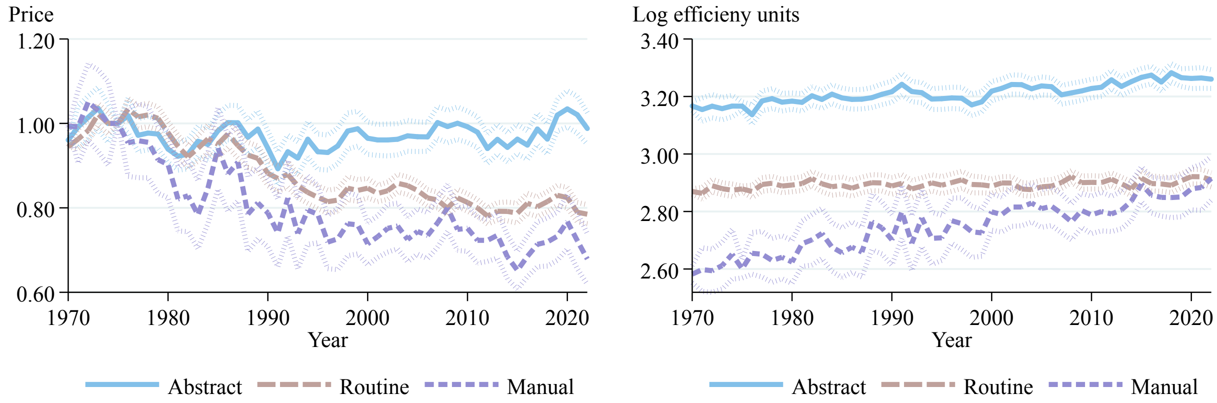
The flat spot approach has an important advantage over alternative methods in estimating price changes over long-term horizons because it provides consistent estimates of prices in the presence of cohort effects. For instance, estimation strategies based on the Roy model of selection require that the population distribution of abilities is stable over time and across different cohorts of workers. The mapping between workers' abilities and their occupational human capital is also required to be stable over the estimation period.[11] While these assumptions might hold in the short run, they are unlikely to hold over the half-century, in which the changes in the wage inequality I study take place. Moreover, the presence of cohort effects in human capital production function documented in Bowlus and Robinson (2012) and Carneiro and Lee (2011) would confound the long-run price change estimates if they are not taken into account.

[11] 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.

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 stable human capital levels over the flat spot region. Second, the skill must be homogeneous within human capital groups, which is plausible given that workers within each occupational group, on average, specialize in their respective tasks during the flat-spot age range (see Appendix J). Third, the wage change for high-tenure workers reflects the market price change and is not driven by contractual arrangements between them and their employers. My analysis of the age dynamics of several non-pecuniary job characteristics like employer-provided health and pension plans for workers in different occupations reveals that contractual differences across occupations are unlikely to affect my results (see Appendix I).

One additional issue associated with applying the flat spot price identification approach to occupation-based human capital relates to occupational switching and the stability of skill groups defined by occupations. 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 small. Using the panel component of MORG files, I show that over 80% of workers in their flat spot age range remain in the same occupational group over a year. This share remains stable across the flat spot age range and over time (see Appendix D). While occupational choice is endogenous and depends on the price and quantity of occupation-specific human capital for workers, I rely on a broad definition of an occupational group that encompasses multiple occupations intensive in abstract, routine, or manual tasks. 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 (see Appendix F). Other studies have also shown that the role of selection in occupation stayers decreases with age as match quality increases with experience.[12]

[12] 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 they face a shortened horizon of future earnings and are more heavily invested in their existing stock of skills.



(a) Price Series

(b) Log Efficiency Units Series

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.

3 Results

Figure 4 shows the estimation results for the prices and quantities of human capital in abstract, routine, and manual occupations over 1970-2022. Figure 4a shows the estimated price series.[13] The prices for all occupations tend to fluctuate and drop during the recessions of the mid-1970s, early 1980s, early 1990s, and COVID. However, clear trends emerge: the price series for manual and routine workers decline over the observed period and are highly correlated ($\rho = 0.89$), while the price series for abstract workers remain relatively stable. Between 1970 and 2022, the prices for routine and manual workers decline by more than 18% and 38%, respectively, while the price for abstract workers increases by 2.8%.

While my estimated price changes for abstract occupations are consistent with the previous literature, the estimated price changes for the manual occupations differ substantially. I quantify that the price for abstract workers relative to routine workers increases by 24 log points between 1980 and 2010, similar to the 25 log points increase in the price of abstract relative to routine

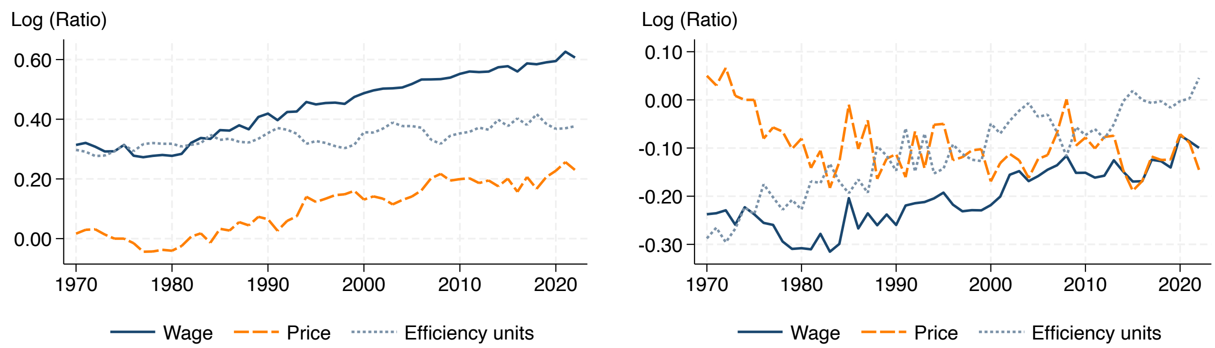
[13] Normalization of the price for one of the years is required. I normalized the prices in 1974 and 1975 to one due to the change in MCPS reporting of weekly hours worked.

human capital between 1984-1992 and 2007-2009 estimated in Böhm (2020), and a 25 log points increase in the price of abstract relative to manual human capital between 1976 and the mid-2000s estimated in Cortes (2016). By contrast, I find a small 0.3 log points increase in the price for manual relative to routine occupations between 1980 and 2010. This finding contrasts with a significant increase in the price for manual occupations relative to routine occupations 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.

My findings differ from the estimates in the previous literature because the flat spot price estimation method that I employ allows for cohort effects in the distribution of human capital supplied by workers. Therefore, changes in wage differentials between occupations can be attributed to shifts in the quantity of human capital supplied by workers and not to the price of human capital. That turns out to be the case for workers in manual occupations, as you can see in Figure 4b, which shows the evolution of log efficiency units of occupational human capital levels per worker. While the human capital level is stable for routine workers, manual workers accumulate human capital at a high rate. Under the assumption of stable human capital distributions in the population, the wage growth generated by this change would be attributed instead to a growing relative price of manual tasks.

A possible explanation for the increase in human capital observed in manual occupations is related to the shift of educational composition towards more educated workers. However, although the average level of schooling has increased in both manual and routine occupations, it was associated with greater human capital growth for manual workers, suggesting that educational composition alone cannot fully explain the divergent human capital trends between these occupations. For manual workers, 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 routine workers. A stronger increase in the college wage premium in manual occupations suggests that later cohorts of college-educated workers in manual occupations were potentially more successful in accumulating human capital than college-educated workers in routine occupations.

Figure 5 decomposes the growth of the log median wage premium of abstract and manual



(a) Abstract Relative to Routine

(b) Manual Relative to Routine

Figure 5: Decomposition of Wage Premium

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 for 95% confidence intervals for the estimated changes between consecutive years.

occupations relative to routine occupations into the change in relative prices and the change in relative log quantities of human capital. Since the 1990s, the growth in the wage premium for abstract occupations relative to routine occupations is driven by an increase in relative prices, which is consistent with the role of the SBTC and RBTC in the rise of the relative demand for abstract tasks and expansion of wage inequality in the upper tail of wage distribution. By contrast, the higher wage growth in manual occupations compared to routine occupations is driven by the faster accumulation of human capital in manual occupations, allowing manual workers to catch up to the human capital levels in routine occupations.[14] This is at odds with the prediction of RBTC increasing the price for manual relative to routine occupational tasks.

Taken together, my findings align with the role of SBTC in increasing the wage premium for high-skilled workers and offer a clear explanation for the decline in human capital prices for college graduates observed by Bowlus and Robinson (2012). As college graduates increasingly enter routine and manual occupations, the price of their human capital becomes differentially affected by what they do in the workplace. I find that while the price for an efficiency unit of college

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

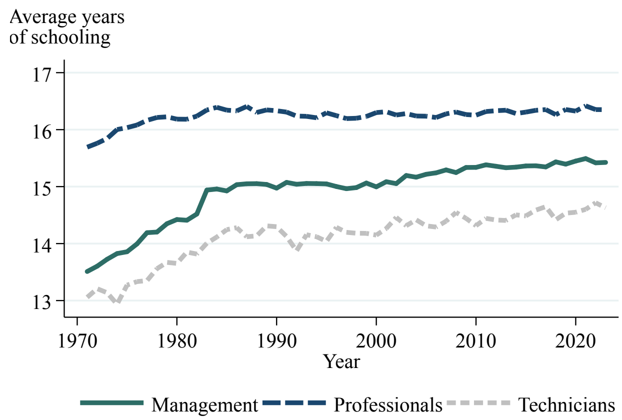


Figure 6: Average Schooling in Abstract Subgroups

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.

workers' human capital in abstract occupations has remained stable since the mid-1990s, it has steadily declined for college-educated workers in routine occupations (see Appendix C). In this way, my results highlight the significant role that heterogeneity among occupations plays in explaining the evolving dynamics of wage inequality among college graduates and provide further evidence that the value of education depends on the task content of workers' occupations.

To find further evidence of changes to the relative demand for high-skill workers, I compare the trends in the price of abstract occupational subgroups. These subgroups incorporate workers in managerial occupations, professional occupations and technicians.[15] Figure 6 shows that among abstract occupations, professional workers have the highest average levels of schooling with at least a one-year schooling gap compared to managerial workers. Professional occupations are dominated by workers with postgraduate degrees often required for jobs like doctors, scientists, and instructors (see Appendix K). These high levels of training as measured by schooling imply that professional workers may be considered the most skilled group across abstract occupations.

Figure 7 shows that even within abstract occupations, the most skilled workers dispro-

[15] Managerial occupations include, for example, accountants, auditors, financial managers, and HR specialists. Professional occupations include architects, scientists, doctors, and instructors, while technician occupations include dental hygienists, legal assistants and paralegals.

portionately benefited from the growing demand for high-skill labour. Workers in professional occupations have experienced the highest increase in the relative price of human capital followed by workers in managerial occupations. Between 1970 and 2022, the price for 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.[16] 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.

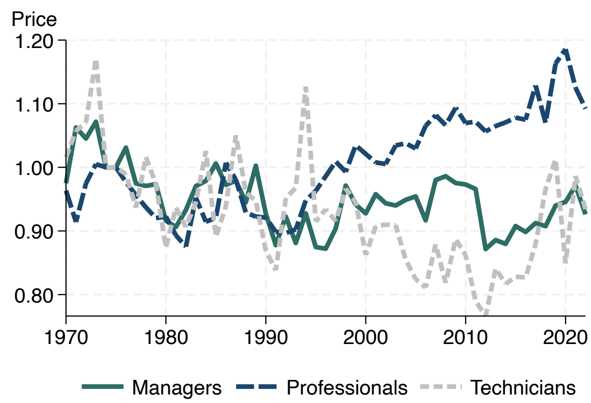


Figure 7: Price Series within the Abstract Group

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 B for 95% confidence intervals for the estimated changes between consecutive years.

4 Conclusion

I reexamined the RBTC and SBTC explanations of the growing wage gaps between high-skill, middle-skill, and low-skill workers by allowing for 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

[16] Appendix B provides these estimates with 95% confidence intervals.

Heckman et al. (1998) and Bowlus and Robinson (2012) on the MCPS data from 1971 to 2023.

My results indicate that wage gaps between workers in abtract, routine, and manual occupations are driven by different forces. The relative price of the abstract occupations has increased relative to both the routine and manual occupations, supporting theories relating the growing inequality to the technological growth stimulating the demand for high-skilled workers. The growth of wages in manual occupations relative to routine occupations emphasized in the 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.

By focusing on workers' occupations rather than education, I explain the puzzling decrease in the price of human capital for college graduates documented in Bowlus and Robinson (2012), driven by their increasing employment in routine and manual occupations exposed to declining human capital prices. Therefore, my findings provide evidence that technological change affects workers differently depending on what they do in the workplace, even if they have similar education levels.

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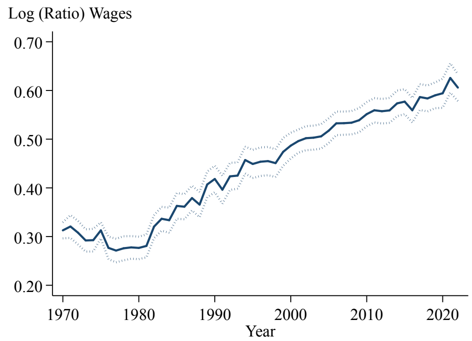
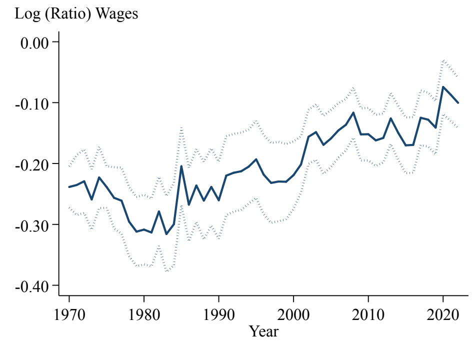
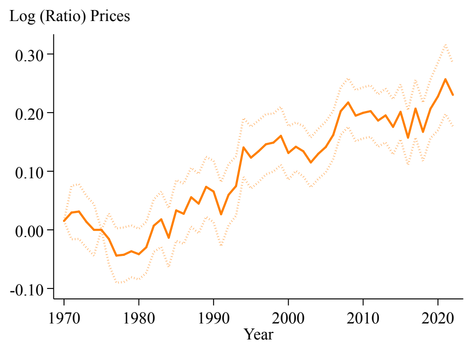
A Confidence Intervals for Decomposition of Relative Wage Changes Between Abstract, Routine, and Manual Groups



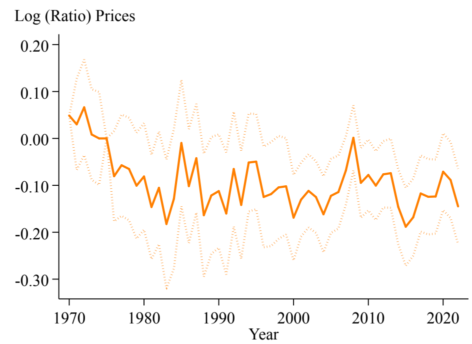
(a) Abs. vs Rout.: Wage



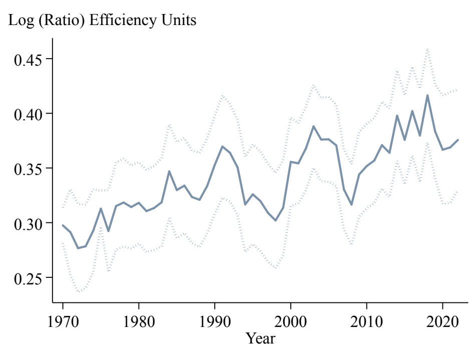
(b) Man. vs Rout.: Wage



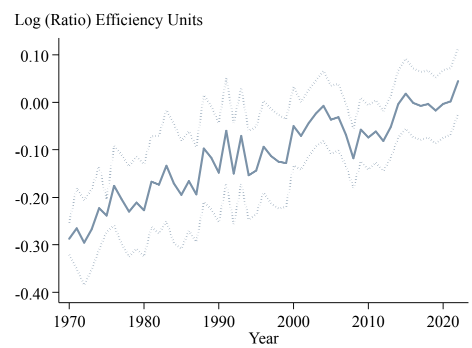
(c) Abs. vs Rout.: Price



(d) Man. vs Rout.: Price



(e) Abs. vs Rout.: EU

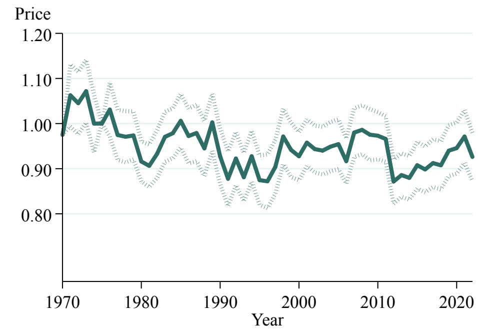


(f) Man. vs Routine:EU

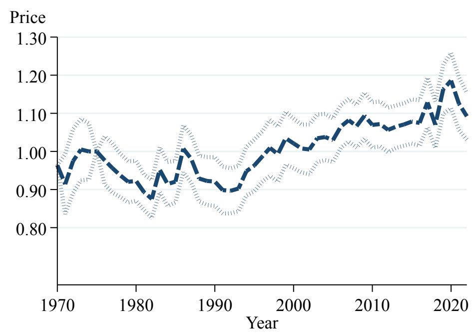
Figure A.1: Confidence Intervals for Decomposition of Wage Premium: Log Relative Wages, Prices, and Efficiency Units

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.

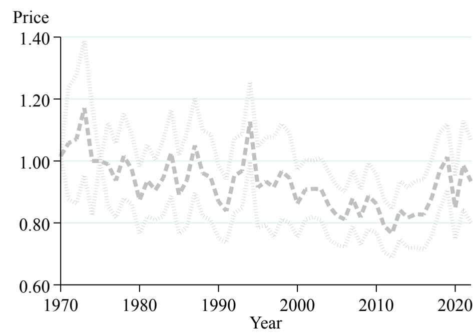
B Confidence Intervals for Prices within Abstract Group



(a) Managerial



(b) Professional



(c) Technicians

Figure B.1: Confidence Intervals for Prices within Abstract Group

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.

C Price Series for College Graduates in Abstract and Routine Occupational Groups

While Bowlus and Robinson (2012) found that the prices of human capital followed similar trends across education, my findings suggest that the trends in the prices of human capital diverged for workers employed in abstract compared to routine and manual occupations. While education is an important characteristics of workers' human capital, the growing wage inequality among college-educated workers underscores the role of other characteristics, including worker's occupations, in explaining changing wage inequality (Lemieux, 2006).

To explore whether defining workers' human capital by occupation enhances the understanding of changes in wage inequality across college workers, I estimate changes in prices for an efficiency unit of human capital for college-educated workers employed in abstract and routine occupations. Following Bowlus and Robinson (2012), I use a subsample of college-educated full-time, full-year male workers ages 50 to 59 to estimate the price series, but I estimate separate price trends for workers employed in abstract and routine occupations.[17]

Figure C.1 shows that the price for an efficiency unit of college worker's human capital in abstract occupations has remained relatively stable after the mid-1990s. By contrast, the price for college-educated workers in routine occupations was steadily declining. While the estimated price series may have limited statistical power due to the reduced sample size after partitioning, the results confirm that wages of workers with the same education level might be differentially affected by changes in the labour markets depending on their occupation.

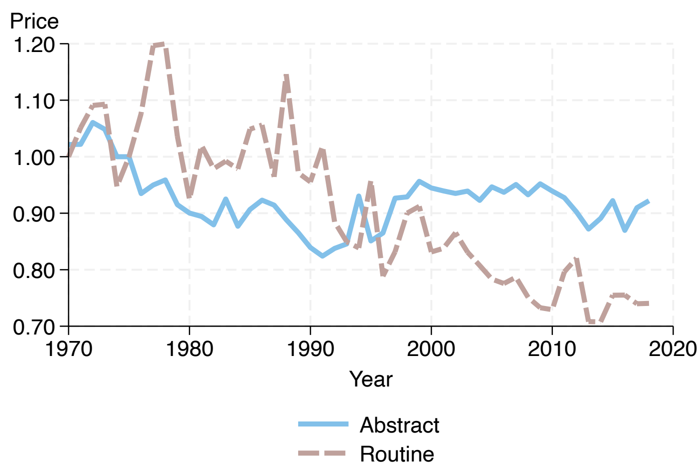
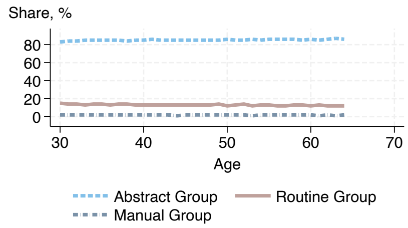


Figure C.1: Price Series for College-educated Workers Employed in Abstract and Routine Occupational Groups

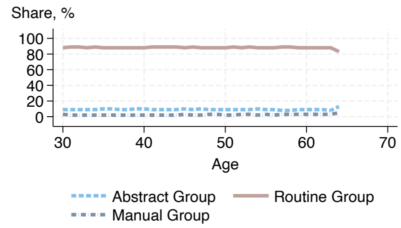
D Occupational Group Switching behaviour

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

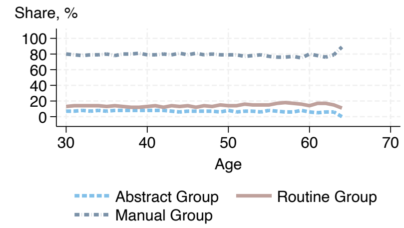
[17] The sample size of college-educated workers in manual occupations is too small to be included in the analysis.



(a) Abstract Group



(b) Routine Group

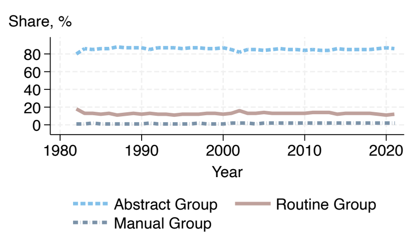


(c) Manual Group

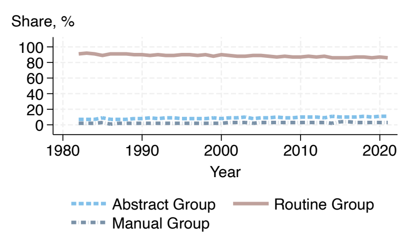
Figure D.1: Occupational Switching Patterns by Occupation Group and Age

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.

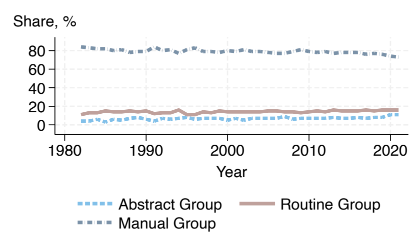
estimation. The MORG samples consist of households who answer additional labour market questions in months four and eight in the Basic Current Population Survey. The responses in month four and month eight can be matched, providing information about changes in labour market outcomes over the year of 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.



(a) Abstract Group



(b) Routine Group

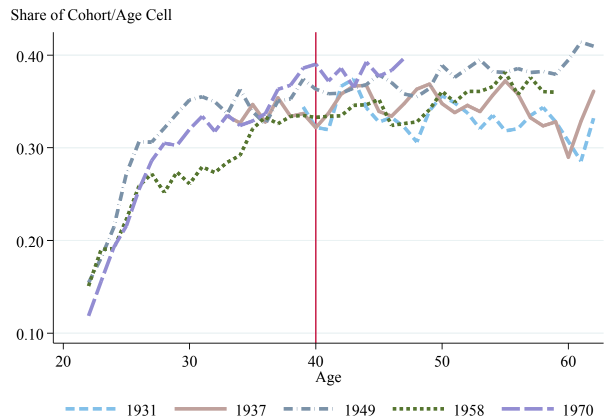


(c) Manual Group

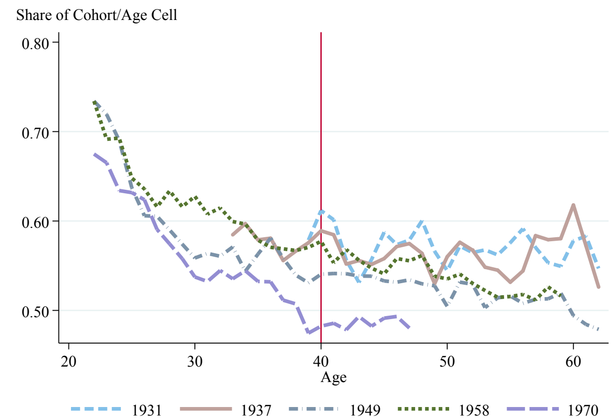
Figure D.2: Occupational Switching Patterns by Occupation Group and Year

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 40-64 in MORG 1982-2022.

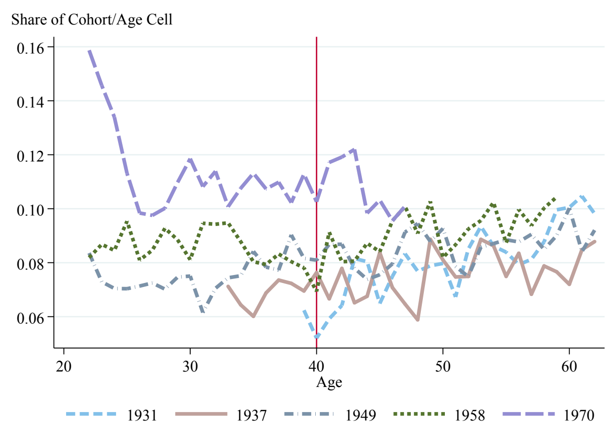
I find that the choice of the broad occupational group is persistent for senior workers. Figure D.1 demonstrates the pattern of occupation group switching for full-time workers employed in abstract, routine, and manual occupations in their month four in the sample. Over 80% of the abstract and routine 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 D.2 additionally shows that this pattern of occupational switching remained stable for workers aged 40 to 64 across the years.



(a) Abstract Group



(b) Routine Group



(c) Manual Group

Figure D.3: Occupational Group Sorting by Birth Cohort

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 D.3 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 limited sample sizes, the occupational structure for all cohorts seems to become more stable by the age of 40. [18]

E 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 E.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 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.

[18] 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.

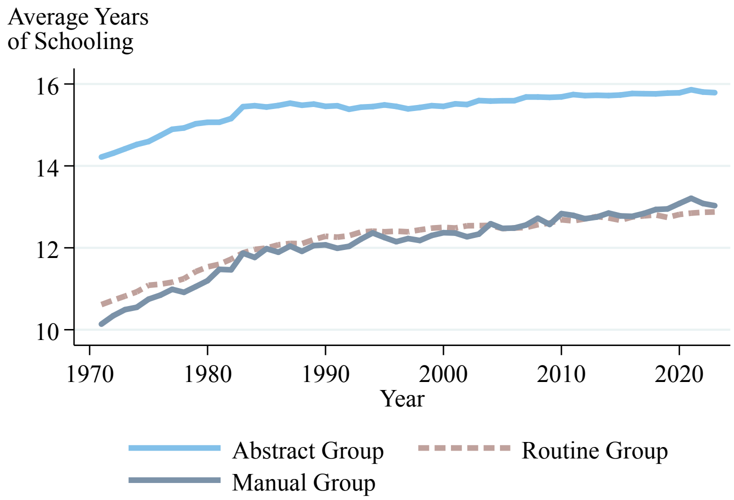


Figure E.1: The Growth of Average Schooling in Occupation Groups

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.

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

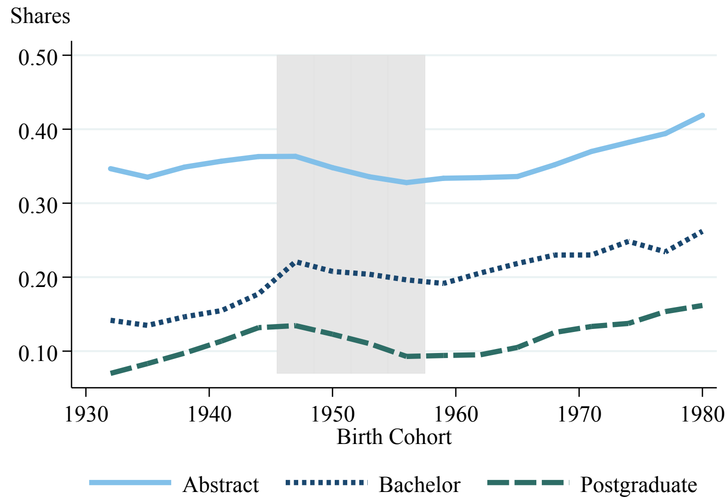


Figure E.2: Share of Abstract Group Workers, Workers with Post-graduate Degrees and a Bachelor Degree by Birth Cohort

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.

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 abstract group. The probability of switching to abstract jobs is increasing in workers' ability

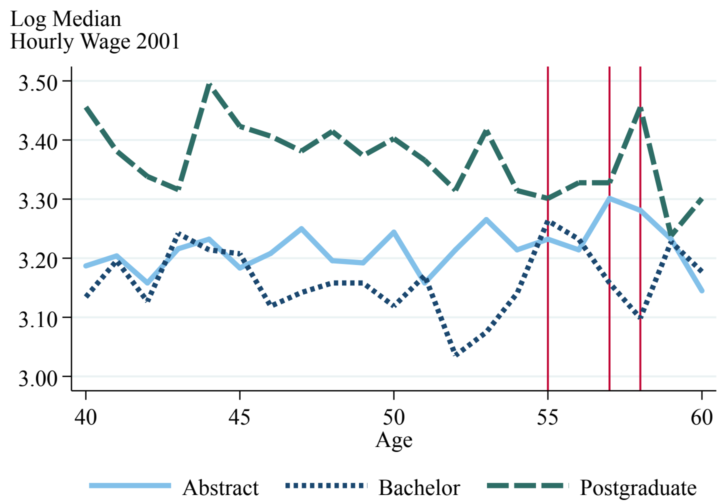


Figure E.3: Log Median Hourly Wage Profile by Age in 2001

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.

(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 E.2 plots the share of FTFY workers between 35 and 40 years old, at the entrance to their potential flat spot age, 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

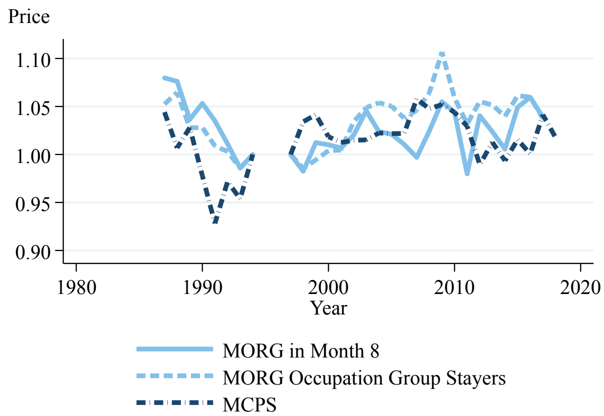
$$lnw_a^c - lnw_{a-1}^{c+1} < \Delta lnS_a.$$

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 E.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.

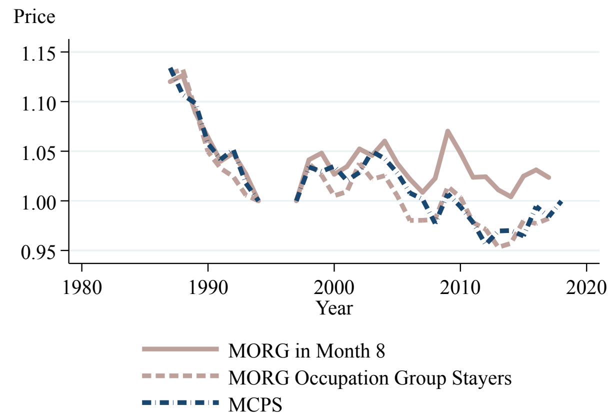
Based on the abstract group's educational composition and the cross-sectional evidence, the abstract group's flat spot range is selected to be 51-60 years old. It starts one year later than the flat spot region for workers with a four-year college degree in Bowlus and Robinson (2012). The sensitivity 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.

F Sensitivity of Price Estimation to Occupational Group Switching

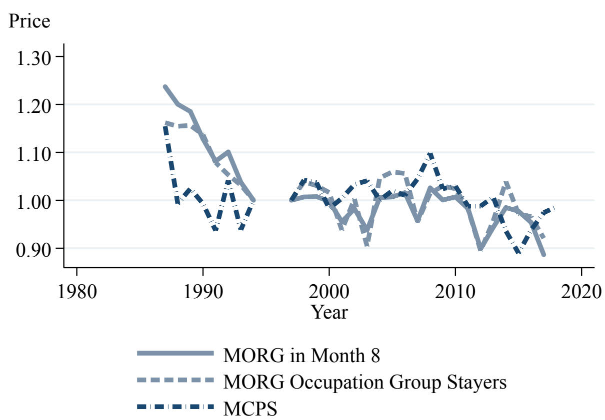
To see whether occupational switching behaviour can significantly alter the estimated price, I estimate the price series for occupational group stayers. Figure F.1 illustrates the benchmark price series estimated for the restricted and unrestricted samples. Unrestricted samples include full-time wage 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.



(a) Abstract Group



(b) Routine Group



(c) Manual Group

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

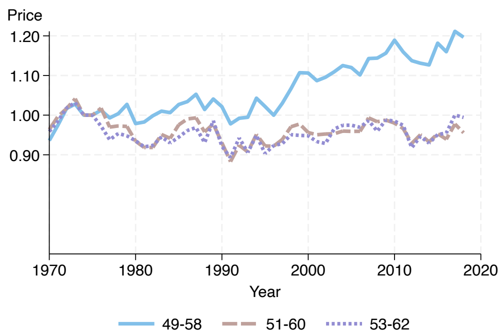
Notes: This figure plots the estimated baseline price series in MCPS along with the price series estimated for the sample of full-time workers in MORG based on wage data collected during month 8 in the sample, and the sample of full-time occupation stayers in MORG based on wage data collected during 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.

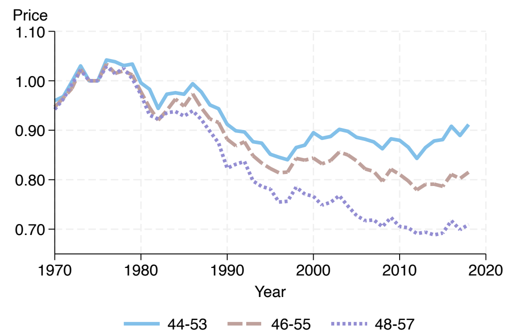
G Sensitivity to Changing the Flat Spot Age Range

This section analyzes the sensitivity of price series estimates to the choice of flat spot region. Figure G.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.

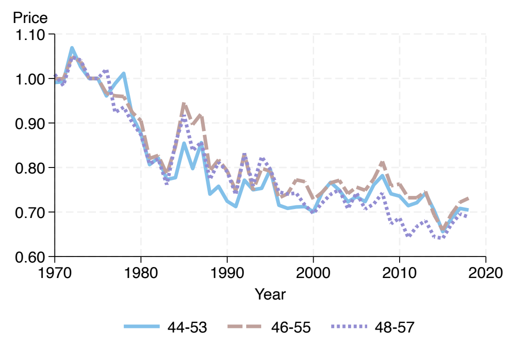
The price series for the routine group follow the expected pattern with early flat spots leading to the overestimation of the price series and late flat spots to underestimation as they potentially capture the effect of human capital depreciation and retirement. The manual occupation group price series 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.



(a) Abstract Group



(b) Routine Group



(c) Manual Group

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

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.

H Wage Measure

The Bureau of labour Statistics (BLS) allocates missing values arising from the non-response using a hot-deck imputation method. Table H.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.

Figure H.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 underesti-

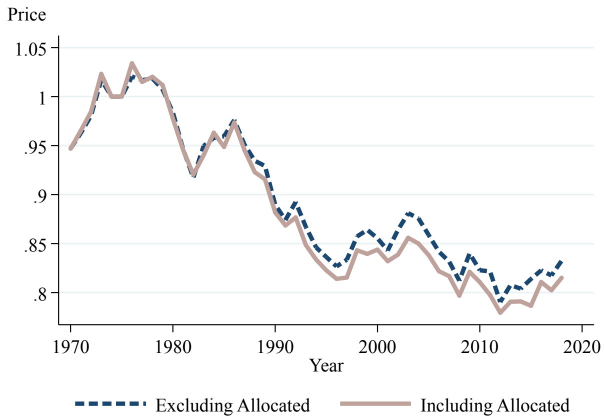
	Abstract Group [51-60 FTFY Male Workers]	Routine Group [46-55 FTFY Male Workers]	Manual Group [46-55 FTFY Male Workers]
Sample Size 1970-2017	95,559	181 353	30 054
Share of allocated values, % 1970-2017	19.5	18.6	19.3

Table H.1: Sample Size and Proportion of Allocated Values for FTFY Workers in Their Flat Spot Age Range

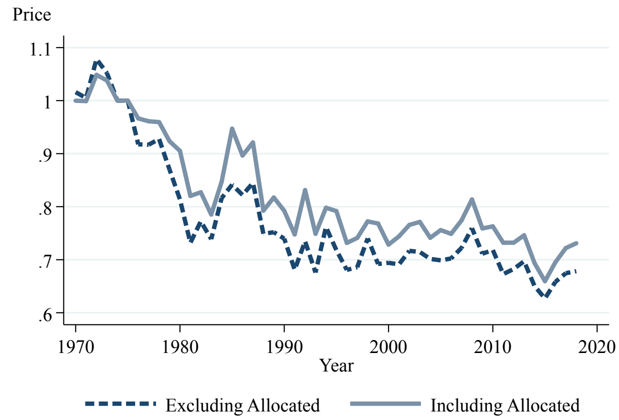
mation of median wages. The earnings observations in the MCPS are missing in a non-random way, with older workers less likely to report their wage.[19] Figure H.2 analyses the patterns of wage allocation for the abstract group. Panel H.2a illustrates the share of allocated value for FTFY abstract group 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 H.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.

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

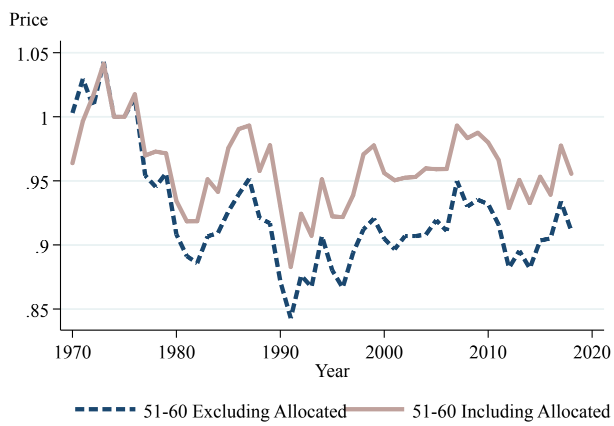
Using the median hourly wages in the estimation allows me to solve the problem of inconsistently top-coded values in the CPS, however, it is common in the labour economics literature to perform the analysis using the average wage and average log wage measures. My findings are robust to the use of alternative wage measures. Figure H.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.



(a) Routine Group



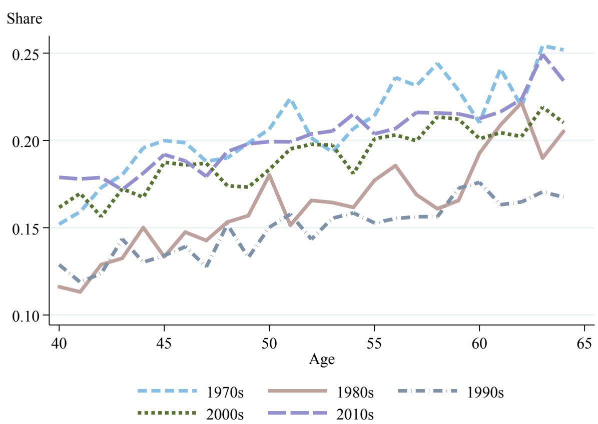
(b) Manual Group



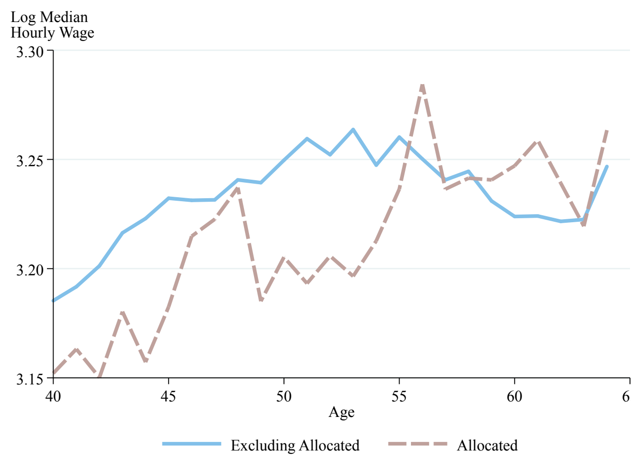
(c) Abstract Group

Figure H.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.



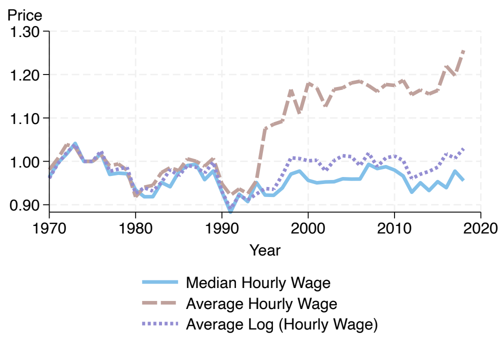
(a) The Share of Allocated Earnings: Age and Decade



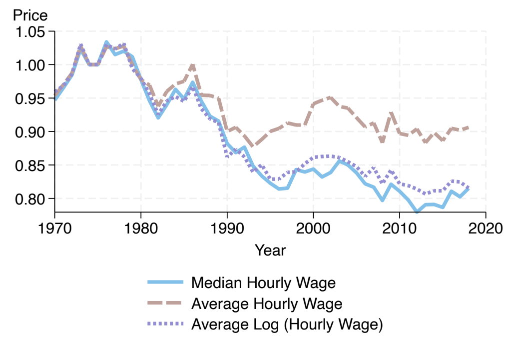
(b) Log Median Hourly Wage by Age: Allocated and Excluding the Allocated Earnings

Figure H.2: Allocated Wages for Abstract Group

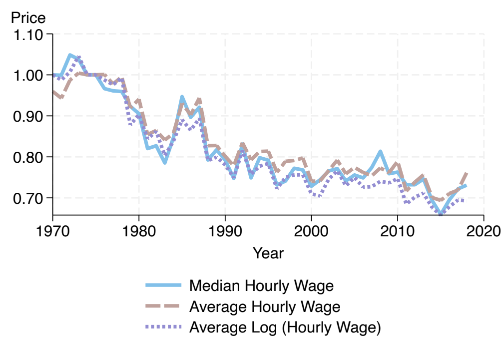
Notes: Panel (a) displays the average share of allocated earning values by age for various survey decades in the abstract group. Panel (b) displays the log median hourly wage by age estimated excluding allocated values and only for allocated values. The sample includes full-time full-year wage and salary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



(a) Abstract Group



(b) Routine Group



(c) Manual Group

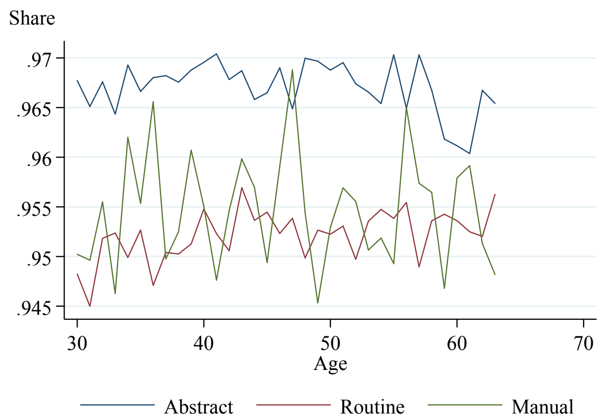
Figure H.3: Sensitivity of Price Series to Using Alternative Wage Measures

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.

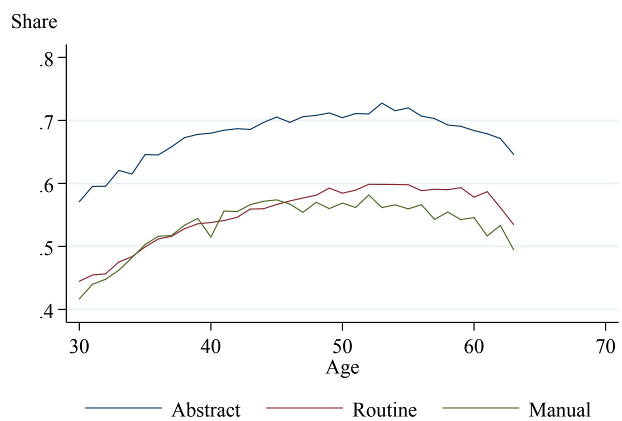
I Differences in Contracts Across Occupational Groups

MCPS asks respondents whether they have access to employer-provided health and pension plans. Figure I.1 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.



(a) Health Plan



(b) Pension Plan

Figure I.1: Share of Workers with Employer-provided Pension and Health Plans by Occupation Group

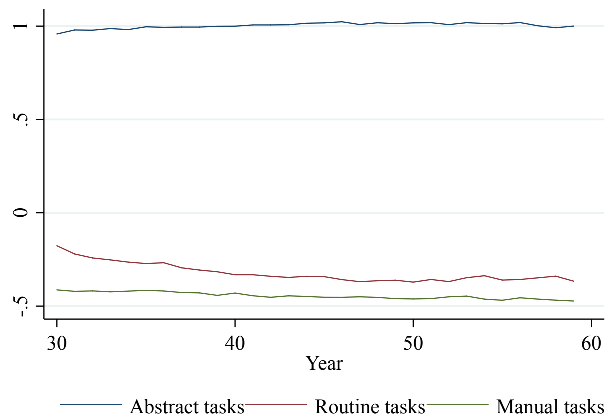
Notes: This figure summarized the average share of workers who report having access to health plans or pension plans at work by age. The sample includes full-time full-year wage and salary male workers in MCPS 1971-2023.

J Differences in Job Tasks Across Occupational Groups

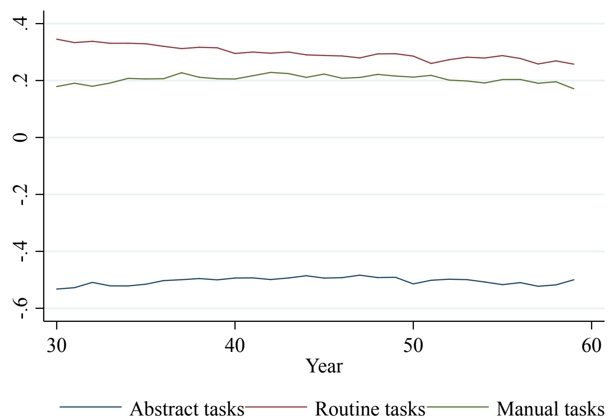
Following Acemoglu and Autor (2011) I sort workers into broadly defined occupational groups based on the Census classification of occupations. While commonly used in the literature (see, for example, Beaudry et al. (2016), Böhm (2020), Cavaglia and Etheridge (2020), and Cortes (2016)), it is possible 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 D.O.T. 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.

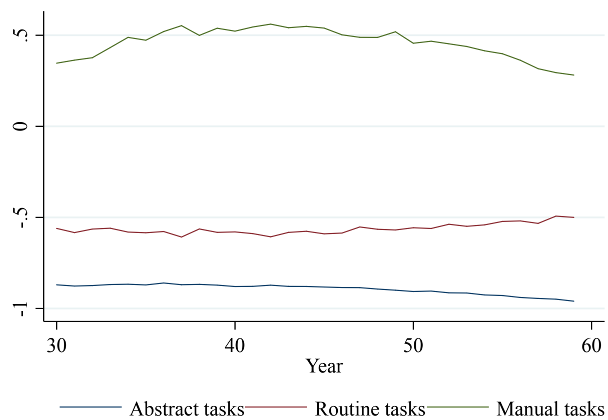
Figure J.1 shows the evolution of the average task intensity for all cohorts of workers by age. The average intensity of abstract tasks exceeds the average intensities of routine and manual tasks for workers in abstract occupational group. Moreover, the intensity of abstract tasks remains stable over 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.



(a) Abstract Group



(b) Routine Group



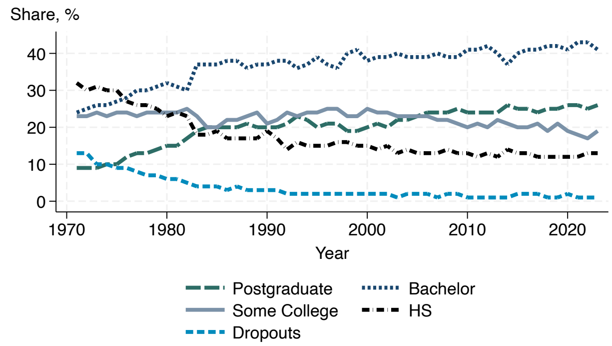
(c) Manual Group

Figure J.1: Average Task Intensity in Occupation Group by Age

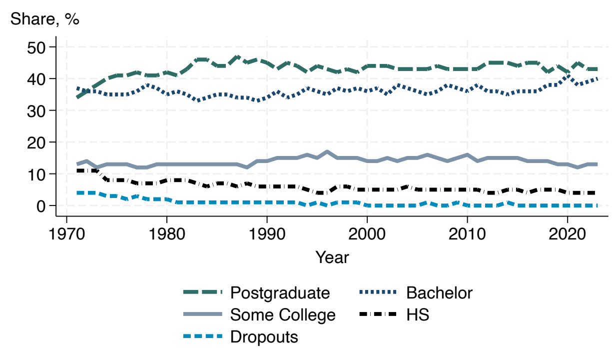
Notes: This figure summarized the life-cycle profile of the average intensity of abstract, routine, and manual tasks by broad occupational group. The tasks are computed using DOT 1977 task data provided in Autor and Dorn (2013). The sample includes full-time full-year wage and salary male workers in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

K Educational Composition by Abstract Occupational Subgroups

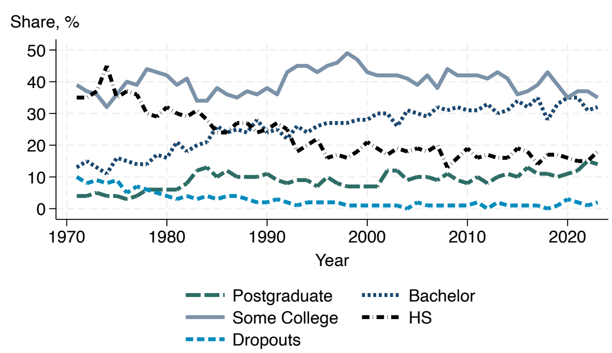
This section analyses the educational composition of occupational subgroups within the abstract group. These subgroups incorporate workers in managerial occupations, professional occupations and technicians. Figure K.1 explores the educational composition of these subgroups, and its evolution between 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.



(a) Managerial



(b) Professional



(c) Technicians

Figure K.1: Educational Composition within Abstract Subgroup

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.

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