

The Evolution of Prices and Quantities of Occupational Human Capital *

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Abstract

I examine the roles of skill- and routine-biased technical change (SBTC and RBTC) in the rising U.S. wage inequality between 1970 and 2022, estimating the evolution of prices and quantities of human capital in occupational groups specializing in abstract, routine, and manual tasks. To quantify changes in prices and quantities of occupation-specific human capital, I use a flat spot price identification method that exploits wage changes for workers approaching retirement to infer shifts in skill prices. Importantly, this method accommodates changes in cohort quality over time, capturing both the effects of shifts in the educational composition of workers in occupations and changes in the quality of education across generations over the study period. The results show that the price for abstract occupations has increased relative to manual and routine occupations, while prices for manual and routine occupations have declined in absolute terms. This evidence supports the role of SBTC in increasing the relative price of high-skill human capital and contradicts the prediction of RBTC increasing the price of manual human capital relative to routine human capital. Moreover, among abstract occupations, professional workers with higher levels of training 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

Over the last five decades, changes in wage inequality in the U.S. 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 have become associated with changing wage differentials between workers employed in occupations with different task content (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007; Acemoglu and Autor, 2011). Specifically, 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 either by shifts in relative prices or by shifts in relative quantities of occupation-specific human capital, neither of which is directly observed by researchers. However, separately identifying changes in the prices and quantities of efficiency units of human capital is important to understanding 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 occupational human capital and low-skill manual occupational human capital relative to 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 through 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 labor markets are more educated and may supply different human capital levels. As university enrollment has expanded and the

information technology revolution has matured, college graduates have “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

In this paper, I reexamine the roles of RBTC and SBTC in explaining the growing wage inequality by allowing for across-cohort changes in the human capital distribution. Using data from the U.S. March Current Population Survey (MCPS) between 1970 and 2022, I estimate the evolution of the prices and quantities of human capital for abstract, routine, and manual occupational groups. I find that during this time period, the price for routine and manual occupations declined by 17% and 31%, respectively, while the price for abstract occupations increased by 2.6%. I show that since the early 1990s, the growth in the relative wage premium for abstract workers compared to routine workers has mainly been driven 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 stems from the growth in the quantity of human capital in manual occupations, contradicting 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 method developed in Heckman, Lochner, and Taber (1998) and Bowlus and Robinson (2012). This price identification method 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, during which changes in hourly

¹For example, Carneiro and Lee (2011) and Hendricks and Schoellman (2018) find that an increase in college enrollment rates leads to significant changes in the average quality of college graduates’ human capital. Bowlus and Robinson (2012) argue that the selection effect from the change in college enrollment rates was accompanied by technological improvement in the human capital production function for college graduate cohorts, improving the human capital quality 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 Gumpert (2016) highlight that university curricula significantly expanded in the late 20th century, 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.

wages are generated solely by skill price fluctuations (Ben-Porath, 1967). A key advantage of this method is that it allows for cohort effects in the production and distribution of human capital. I modify this method, which was originally developed for 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 can quantify how changes in both the prices and quantities of human capital contribute to the evolving wage inequality over the last five decades. Additionally, by focusing on workers' occupations rather than education, I provide evidence that technological change affects workers differently depending on the task content of their occupations, 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 those of 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. However, 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.

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

³Böhm (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 routine occupations.

Further, I show that the increase in the price for 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 12 log points, while prices for managerial occupations slightly declined. Although 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 has increasingly benefited the productivity of high-skill workers at the top of the wage distribution.

This rest of the paper proceeds as follows. Section 2 explains how the flat spot price identification methodology is applied to occupational groups and motivates the use of the MCPS data. Section 3 discusses the results, including the estimates of the price and quantity series, and the implications of the identified trends for the SBTC and RBTC explanations of the growing wage inequality. Section 4 concludes.

2 Data and Methodology

2.1 Data and Summary Statistics

I obtain data on wages, labor supply, and occupational choices of U.S. workers from the MCPS (Flood et al., 2024), which provides the longest available data series on the social and economic indicators of the U.S. labor force. These employment data allow me to consistently control for the annual labor supply of workers and avoid issues concerning workers' selection into part-time jobs and retirement.⁵

⁴Autor et al. (2008) argue that while the earnings of workers with postgraduate degrees had been 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 exhibit different wage trends, with the return for workers with postgraduate degrees rising relative to those with bachelor's degrees.

⁵I also use data from the Merged Outgoing Rotation Group (MORG) dataset, which provides measures of income and supply of labor. However, data on the number of weeks worked annually are available for only 12% of earners who report their earnings as an annual amount, which limits the potential to select individuals with strong labor

Following Bowlus and Robinson (2012), I construct an hourly wage measure by dividing inflation-adjusted annual earnings by annual labor supply.⁶ I focus on the sample of male workers aged 30–64 years who are employed full time for the entire year, i.e., working 35-plus hours per week and 40-plus weeks per year. Additionally, I exclude self-employed workers and workers without records of occupation, annual earnings, and variables used to construct the measure of annual hours worked. Median hourly wages are used for the price series estimation to address the issue of 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 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), based on the 1990 CPS occupational classification. 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 (e.g., Beaudry et al., 2016; Böhm, 2020; Cavaglia and Etheridge, 2020; Cortes, 2016).⁸ The abstract occupational group includes workers in managerial, professional, and technical occupations. The routine occupational group includes workers in sales, clerical, and administrative; and production, crafts, repair, and operative occupations. Finally, the manual occupational group includes workers in service occupations.

Figure 1 depicts the sample’s age and occupational composition. 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 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 fluctuate between market attachment.

⁶ The annual labor supply is calculated as a product of weeks worked last year and hours typically 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 the occupational coding for 1971–1982, 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 an alternative cross-walk based on Autor and Dorn (2013).

⁸In Appendix K, I analyze the average task intensity across occupational groups based on Dictionary of Occupational Titles data. I find that workers in each occupational group tend to specialize in tasks according to their classification. For example, the abstract occupational group has the highest average intensity of abstract tasks.

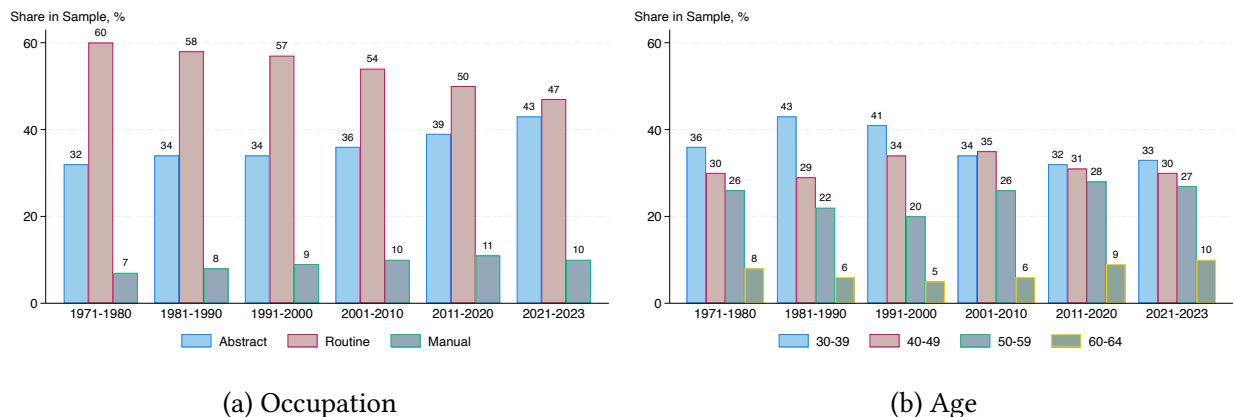


Figure 1: Sample Composition by Decade

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

29% and 35%, while those in their 50s account for 20%–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 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). These changes underscore the importance of accounting for the role of cohort effects in price estimation.

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

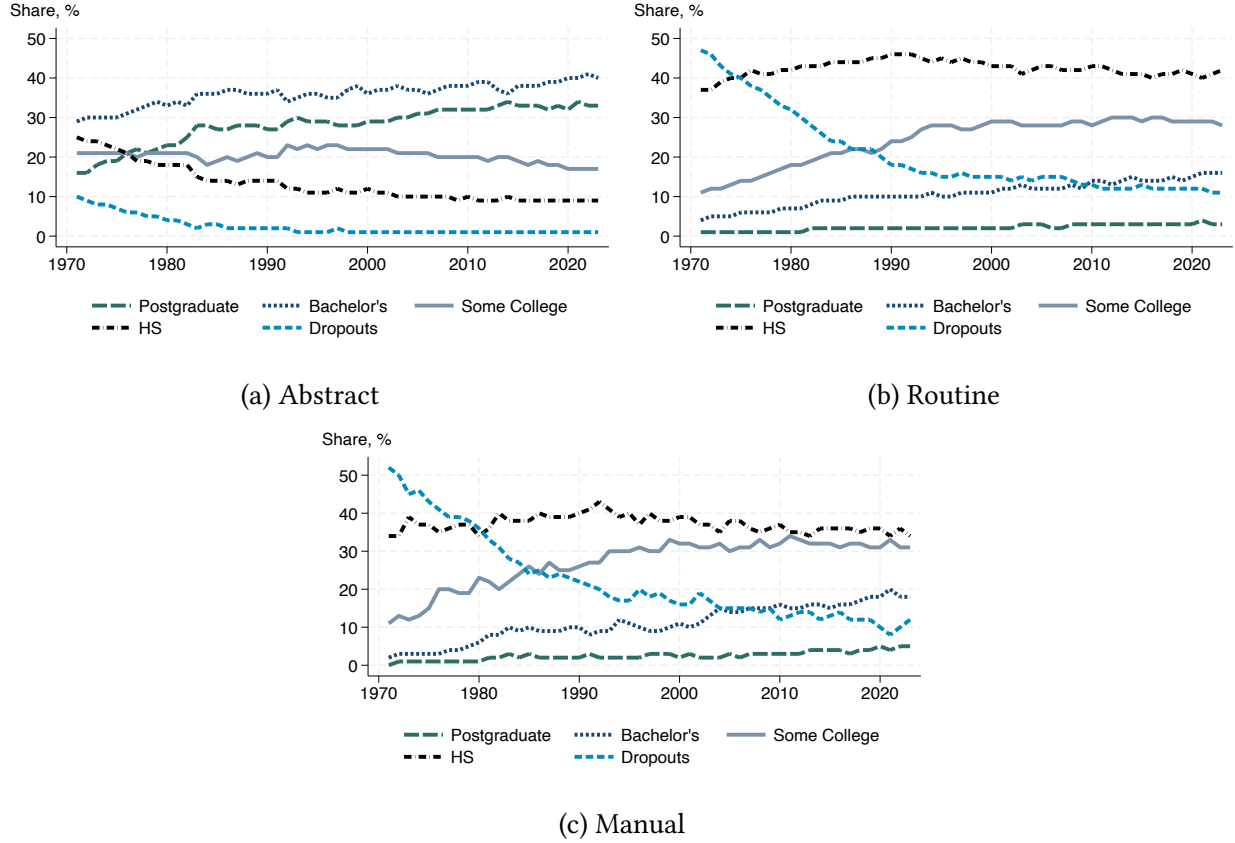


Figure 2: Educational Composition by Occupational Group

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 male wage and salary workers aged 30–64 years in the MCPS. The sample excludes self-employed workers and workers without records of occupation, annual earnings, and annual hours worked.

hourly wage increases for abstract workers and decreases 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 show a stronger decrease in the median log wage than manual workers, and therefore the wage premium for routine occupations relative to manual occupations declines.

2.2 Methodology

The hourly wage earned by a worker employed in a given occupation depends on both the quantity of occupation-specific skill they possess and how the market values this skill. Formally, the period t hourly wage for worker i of age a is the product of their supplied level of efficiency units

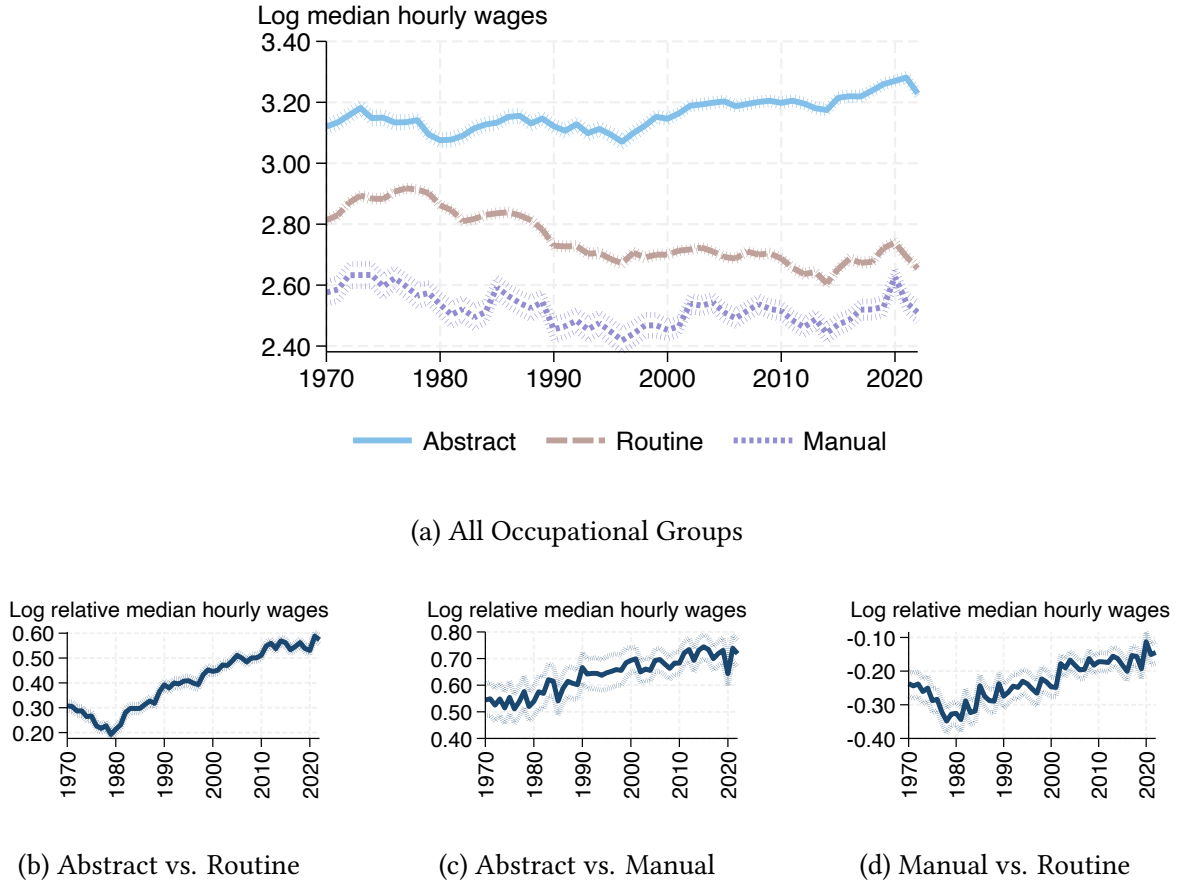


Figure 3: The Evolution of the Log Median Hourly Wage

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

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:

$$Wage_{i,t}^{o,a} = P_t^o \times H_{i,t}^{o,a}. \quad (1)$$

Therefore, the observed changes in wages and wage inequality can be driven either by shifts in the prices for an efficiency unit of occupational human capital or by changes in workers' human capital levels, neither of which are directly observed in the data. Moreover, different cohorts of workers likely differ in their human capital distribution due to dramatic shifts in ed-

educational composition across time and technological and methodological advancements in 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). This method builds on the Ben-Porath (1967) human capital investment model, which predicts that gains from human capital investment decline as workers approach retirement. 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,

$$E[\ln H_{i,t}^{o,a^*} - \ln H_{i,t-1}^{o,a^*-1}] = 0, \quad (2)$$

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

$$E[\ln W_{i,t}^{o,a^*} - \ln W_{i,t-1}^{o,a^*-1}] = \ln P_t^o - \ln P_{t-1}^o. \quad (3)$$

I use this identification assumption 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 the 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. Second, the wage growth rate for a synthetic cohort of workers in period t is computed as the change between the log median wage of workers in year

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

t averaged across all ages and the log median wage of workers in year $t - 1$ averaged across all ages. Finally, the change in the log efficiency units of human capital is computed as the difference between the change in the log median wages and the 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 age range is set too early, the price estimates are biased upward as human capital accumulation by workers increases the wage. If it is set too late, the price estimates are biased downward due to the impact of human capital depreciation on wage growth. To identify the flat spot region, I build on the relationship between labor 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 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 Figure F.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 as 46–55 years 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's degrees in abstract occupations increases from 27% in 1971 to 40% in 2023. Moreover, workers with postgraduate degrees consistently find 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 50 to 59—that of college graduates in Bowlus and Robinson (2012)—to ages 53–62 (see Appendix Figure H.1a).

Furthermore, to narrow down the flat spot age range for abstract occupations, I use the

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

prediction from Bowlus and Robinson (2012) that if the share of the highest skill group contracts across consecutive cohorts, the cohort effect on the 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, reveal 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 F).

2.3 Discussion of the 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 remain 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, during which the changes in the wage inequality I study take place. Moreover, the presence of cohort effects in the 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 considered.

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

¹¹ These strategies require an exclusion restriction that after adding a control function (Böhm, 2020) or fixed effects (Cortes, 2016; Cavaglia and Etheridge, 2020), the price change for a unit of human capital can be identified from the wage regression.

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 K). 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, such as employer-sponsored group health and pension plans for workers in different occupations, reveals that contractual differences across occupations are unlikely to affect my results (see Appendix J).

One additional issue associated with applying the flat spot price identification method 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 find 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 E). While occupational choice is endogenous and depends on the prices and quantities 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 G). Other studies have also shown that the role of selection in occupation stayers decreases with age as match quality increases with experience.¹²

3 Results

Figure 4 presents the estimation results for the prices and quantities of human capital in abstract, routine, and manual occupations over 1970–2022. Panel 4a shows the estimated price series.¹³ The

¹² Gathmann and Schönberg (2010) find that the frequency and distance of occupational changes decline with age. Cavounidis and Lang (2020) show that in a dynamic skill formation model, workers' responses to wage shocks decline with age because they face a shortened horizon of future earnings and are more heavily invested in their existing stock of skills.

¹³ The price must be normalized for one of the years. I also normalize prices in 1974 and 1975 to 1 due to the change in the MCPS' reporting of weekly hours worked.

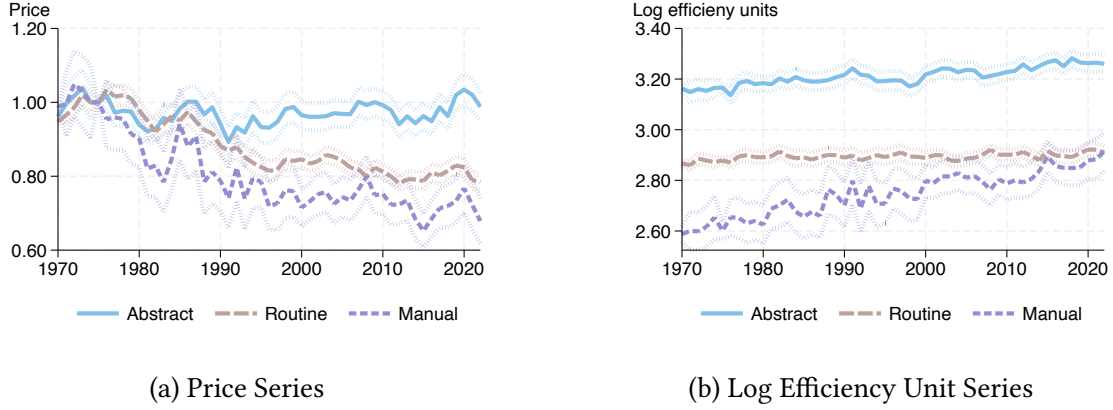


Figure 4: The Evolution of the Prices and Quantities of Occupational Human Capital

Notes: This figure shows 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 male wage and salary workers in their flat spot age range in the MCPS. The figure displays 95% confidence intervals for the estimated change in prices and log efficiency units of human capital between consecutive years.

prices for all occupations tend to fluctuate and drop during the recessions of the mid-1970s, early 1980s, early 1990s, and 2020–2022. However, clear trends emerge: the price series for manual and routine workers decline over the observed period and are highly correlated ($\rho = 0.9$), while the price series for abstract workers remain relatively stable. Between 1970 and 2022, prices for routine and manual workers decline by more than 17% and 31%, respectively, while the price for abstract workers increases by 2.6%.

While my estimated price changes for abstract occupations are consistent with the previous literature, they differ substantially for manual occupations. I quantify that the price for abstract workers relative to routine workers increases by 24 log points between 1980 and 2010, similar to both the 25 log point increase in the price of abstract human capital relative to routine human capital between 1984–1992 and 2007–2009 estimated in Böhm (2020) and the 25 log point increase in the price of abstract human capital relative to manual human capital between 1976 and the mid-2000s estimated in Cortes (2016). By contrast, I find a small 0.3 log point increase in the price for manual occupations relative to routine occupations between 1980 and 2010. This finding contrasts with the 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 estimates in the previous literature because the flat spot price estimation method I use 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 rather than to the price of human capital. This is particularly evident for workers in manual occupations, as shown in Figure 4b, which illustrates 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 instead be attributed to a growing relative price of manual tasks.

A possible explanation for the increase in human capital observed in manual occupations is the shift of educational composition toward more educated workers. However, although the average level of schooling increases in both manual and routine occupations, it is 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 increases by 47 log points between 1970 and 2018, compared to only 13 log point 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 are 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 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 roles of SBTC and RBTC in the rise of the relative demand for abstract tasks and the expansion of wage inequality in the upper tail of the wage distribution. By contrast, the higher wage growth in manual occupations compared to routine occupations is driven by the

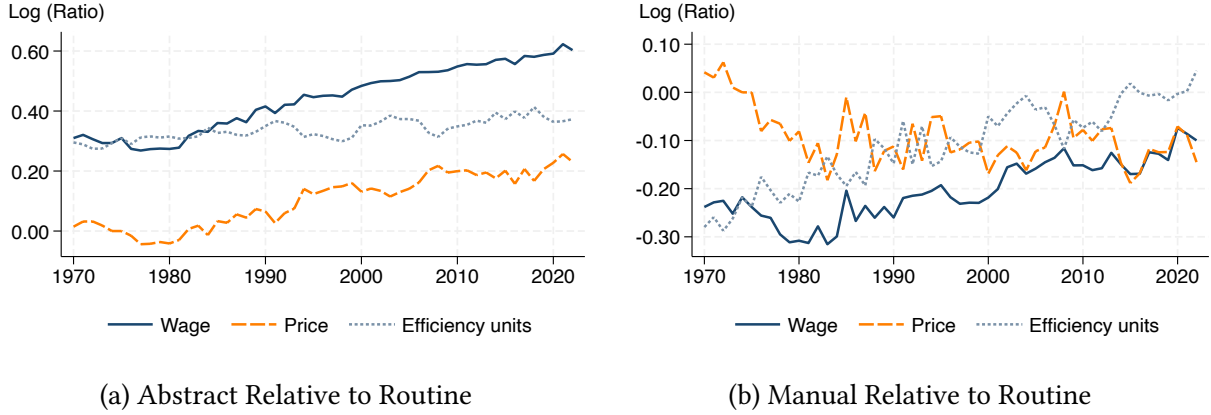


Figure 5: Decomposition of Wage Premium

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

faster accumulation of human capital in manual occupations, allowing manual workers to catch up to the human capital levels in routine occupations. This contradicts 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-skill 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 the task content of their occupations. I find that while the price for an efficiency unit of college-educated 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 D). In this way, my results highlight the significant role of heterogeneity among occupations 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 in the relative demand for high-skill workers, I compare

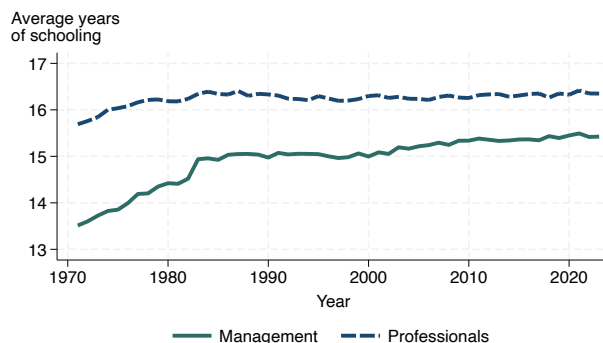


Figure 6: Average Schooling in Abstract Subgroups

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

the trends in the price of abstract occupational subgroups, which include workers in managerial and professional occupations.¹⁴ The results, presented in Figure 6, show 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 positions such as doctors, scientists, and instructors (see Appendix L). 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 disproportionately benefit from the growing demand for high-skill labor. Between 1970 and 2022, the price for professional workers with the highest average levels of schooling in abstract occupations increases by 12 log points, while prices for managerial occupations slightly decline. 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 stems from an increase in the relative price, which corroborates the presence of SBTC.

¹⁴Managerial occupations include accountants, auditors, financial managers, and HR specialists. Professional occupations include architects, scientists, doctors, and instructors. Results for workers in technician occupations, who are also part of abstract occupations, are not reported due to small sample sizes but align with the findings in this section.

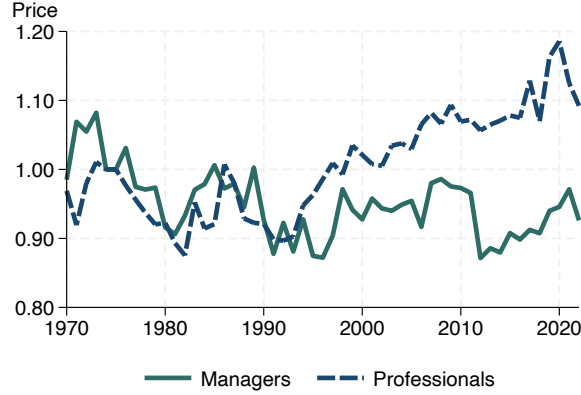


Figure 7: Price Series within the Abstract Occupational Group

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

4 Conclusion

I examine the RBTC and SBTC explanations of the growing wage inequality between high-, middle-, and low-skill workers by allowing for across-cohort changes in the distribution of human capital. Applying the flat spot price identification method developed in Heckman et al. (1998) and Bowlus and Robinson (2012) to MCPS data from 1971 to 2023, I estimate the evolution of prices and quantities of human capital for abstract, routine, and manual groups.

The results indicate that wage inequality between workers in abstract, routine, and manual occupations is driven by different forces. The price of abstract occupations increased relative to both routine and manual occupations, supporting theories relating the growing inequality to technological growth stimulating the demand for high-skill workers. Additionally, the increase in 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 by increases in relative prices. Together, these findings are consistent with the SBTC explanation of the growing wage 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 the task content of their occupations, even among those with similar education levels.

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Appendix: The Evolution of Prices and Quantities of Occupational Human Capital

A Data: Imputing Consistent Annual Hours Worked in the MCPS

For surveys conducted after 1976, the MCPS reports the exact number of weeks the respondent worked for profit, pay, or as an unpaid family worker during the preceding calendar year. However, before 1976, this information was only provided in intervals. To estimate the number of weeks worked for years prior to 1976, I assign a value based on the mean number of weeks worked by wage and salaried workers aged 16 to 64 years with positive earnings and valid occupations within the corresponding intervals in 1976–2023.

Interval	Assigned Number of Weeks
1 - 13 weeks	8.2
14-26 weeks	21.5
27-39 weeks	33.5
40-47 weeks	42.5
48-49 weeks	48.3
50-52 weeks	51.9

Table A.1: Extrapolation of weeks worked last year prior to 1976 based on reported intervals.

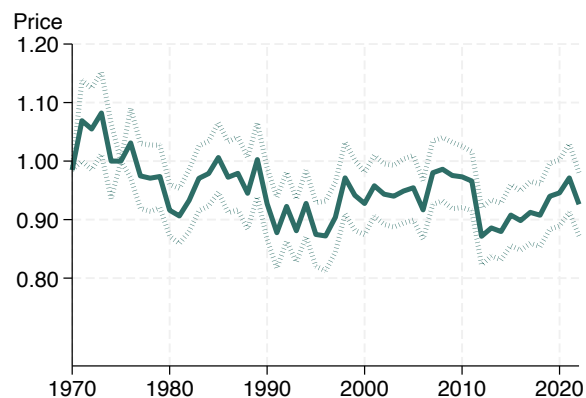
Note: The assigned number of weeks corresponds to the average weeks worked within each interval for wage and salaried workers aged 16 to 64 with positive earnings and valid occupations, based on the MCPS data from 1976–2023.

For surveys conducted after 1976, the MCPS reports the number of hours per week that respondents *usually worked* if they were employed during the previous calendar year. However, for surveys prior to 1976, the MCPS only reports the total number of hours respondents worked *during the previous week*. To impute the usual hours per week last year for respondents in the pre-1976 surveys, I follow a two-step approach.

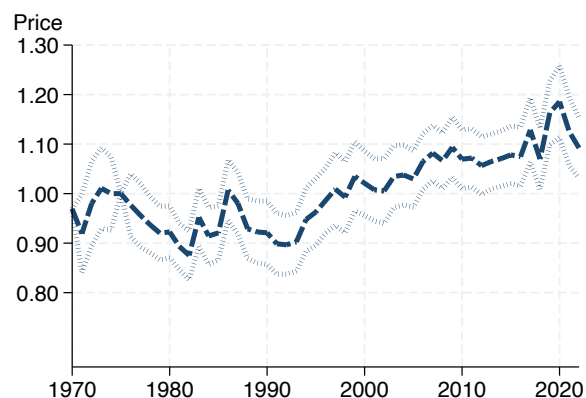
First, for workers who reported positive hours worked last week, their “hours last week” is used as an estimate for “usual hours per week last year.” Second, for workers who did not report positive hours last week but worked last year, I predict their “usual hours per week last year” using a regression of “hours last week” on age, years of schooling, gender, and an occupational group indicator for each survey year from 1971 to 1975. The sample for regressions includes wage

and salaried workers aged 16 to 64 years with positive earnings and valid occupations.

B Confidence Intervals: Prices for Professionals and Managers



(a) Managerial

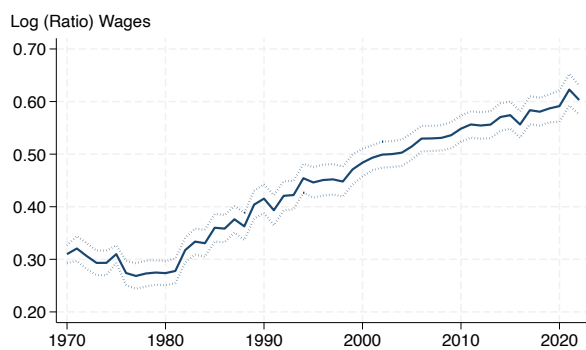


(b) Professional

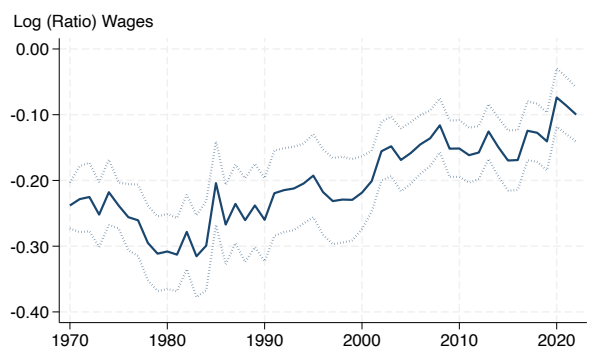
Figure B.1: Confidence Intervals: Prices for Professionals and Managers

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

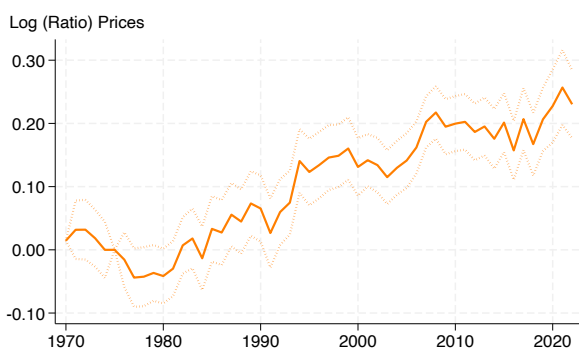
C Confidence Intervals: Decomposition of Relative Wage



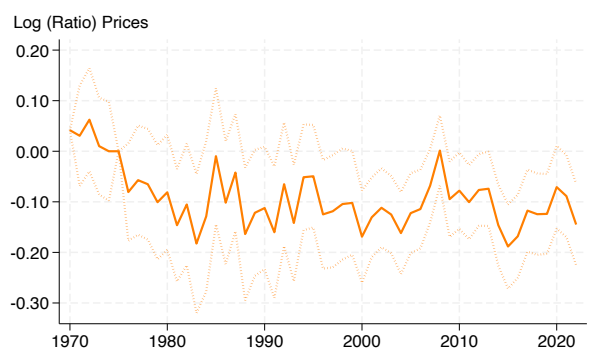
(a) Abs. vs Rout.: Wage



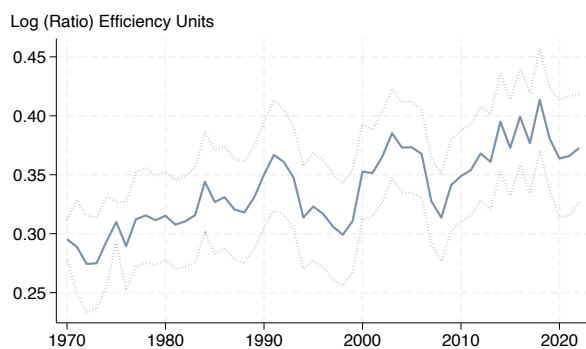
(b) Man. vs Rout.: Wage



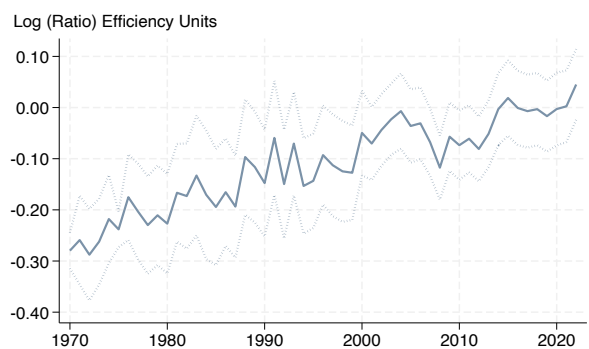
(c) Abs. vs Rout.: Price



(d) Man. vs Rout.: Price



(e) Abs. vs Rout.: EU



(f) Man. vs Rout.: EU

Figure C.1: Confidence Intervals: Decomposition of Wage Premium

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

D Prices for College Graduates in Abstract and Routine Occupations

Although Bowlus and Robinson (2012) found that human capital prices followed similar trends across education, my findings suggest that human capital price trends diverged for workers employed in abstract compared to routine and manual occupations. While education is an important characteristic of workers' human capital, the growing wage inequality among college-educated workers underscores the role of other characteristics, including occupations of workers, in explaining the change in 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 workers with bachelor's degrees employed in abstract and routine occupations. Following Bowlus and Robinson (2012), I use a subsample of full-time, full-year male workers ages 50 to 59 with bachelor's degrees to estimate the price series, but I estimate separate price trends for workers employed in abstract and routine occupations.¹⁵

Figure D.1 shows that the price for workers in abstract occupations has remained relatively stable since the mid-1990s. By contrast, the price for workers in routine occupations has been steadily declining. Although the estimated price series has limited statistical power due to the reduced sample size after partitioning, the results are consistent with the idea that wages of workers with the same education level may be differentially affected by changes in the labor market depending on the tasks they perform in the workplace.

¹⁵The analysis for college-educated workers in manual occupations was excluded due to insufficient sample sizes.

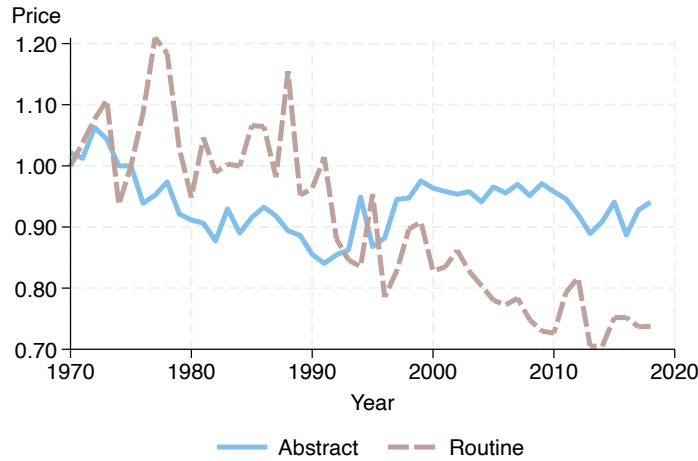


Figure D.1: Price Series for Workers with Bachelor's Degrees in Abstract and Routine Occupations

Notes: This figure displays the evolution of estimated prices of human capital for workers with bachelor's degrees employed in abstract and routine occupations. The sample includes full-time, full-year male wage and salary workers aged 50–59 years in the MCPS.

E Occupational Group Switching Behaviour

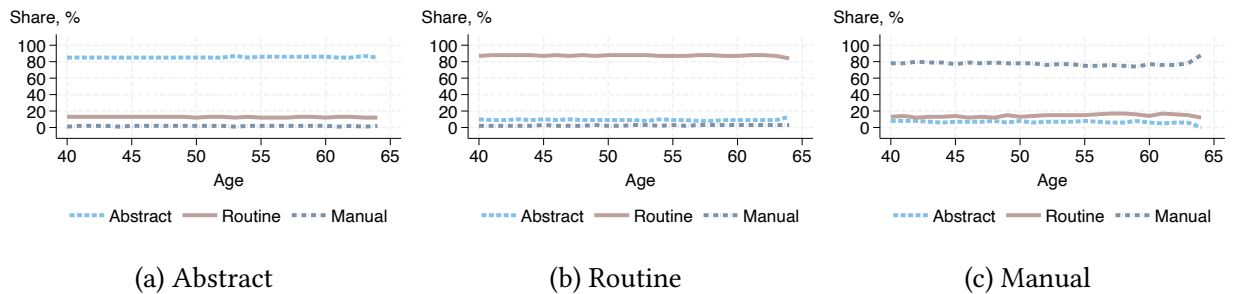


Figure E.1: Occupational Switching Patterns by Age

This figure shows the annual pattern of occupational switching between months 4 and 8 in MORG by age. The sample includes full-time wage and salaried male workers aged 40–64 years from MORG (1986–2022), excluding 1994 and 1995.

If senior workers actively switch occupations, the assumption of stable and homogeneous occupational human capital is unlikely to hold. I use the longitudinal component of the Merged Outgoing Rotation Group (MORG) data from 1982 to 2022 to analyze the role of occupational group switching behavior in price estimation. The MORG samples consist of households who answer additional labor market questions in months four and eight in the Basic Current Population Survey (CPS). The responses in month four and month eight can be matched, providing

information about changes in labor market outcomes over the year of participation in the survey. I restrict the MORG sample to full-time male wage and salaried workers ages 40 to 64 years, who have reported positive earnings and hours worked and had a valid record of occupation.¹⁶

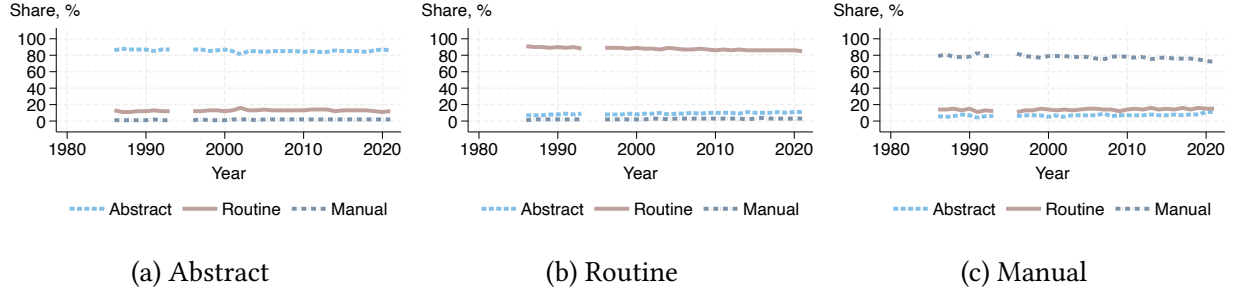


Figure E.2: Occupational Switching Patterns Over Time

This figure shows the annual pattern of occupational switching between months 4 and 8 in MORG over time. The sample includes full-time wage and salaried male workers aged 40–64 years from MORG (1986–2022), excluding 1994 and 1995.

I find that the choice of the broad occupational group is persistent over age and time. Figure E.1 demonstrates the pattern of occupational switching for full-time workers employed in abstract, routine, and manual occupations in month four in the sample. Over 80% of the abstract and routine group workers remain in their occupational groups over the year. Approximately 80% of the workers in manual occupations also persist in their choice of occupational group. Figure E.2 shows that this pattern of occupational switching remained stable for workers aged 40 to 64 years over time.

Figure E.3 analyzes the occupational composition of workers by age and birth cohort. It shows that workers tend to begin their careers in routine or manual occupations and switch to abstract occupations at later stages of their careers. 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 40.¹⁷

¹⁶ Full-time employment is defined as working 35-plus hours per week.

¹⁷ The increase in the share of employment in abstract occupations for workers in their 20s is also a result of abstract workers taking longer to complete their education.

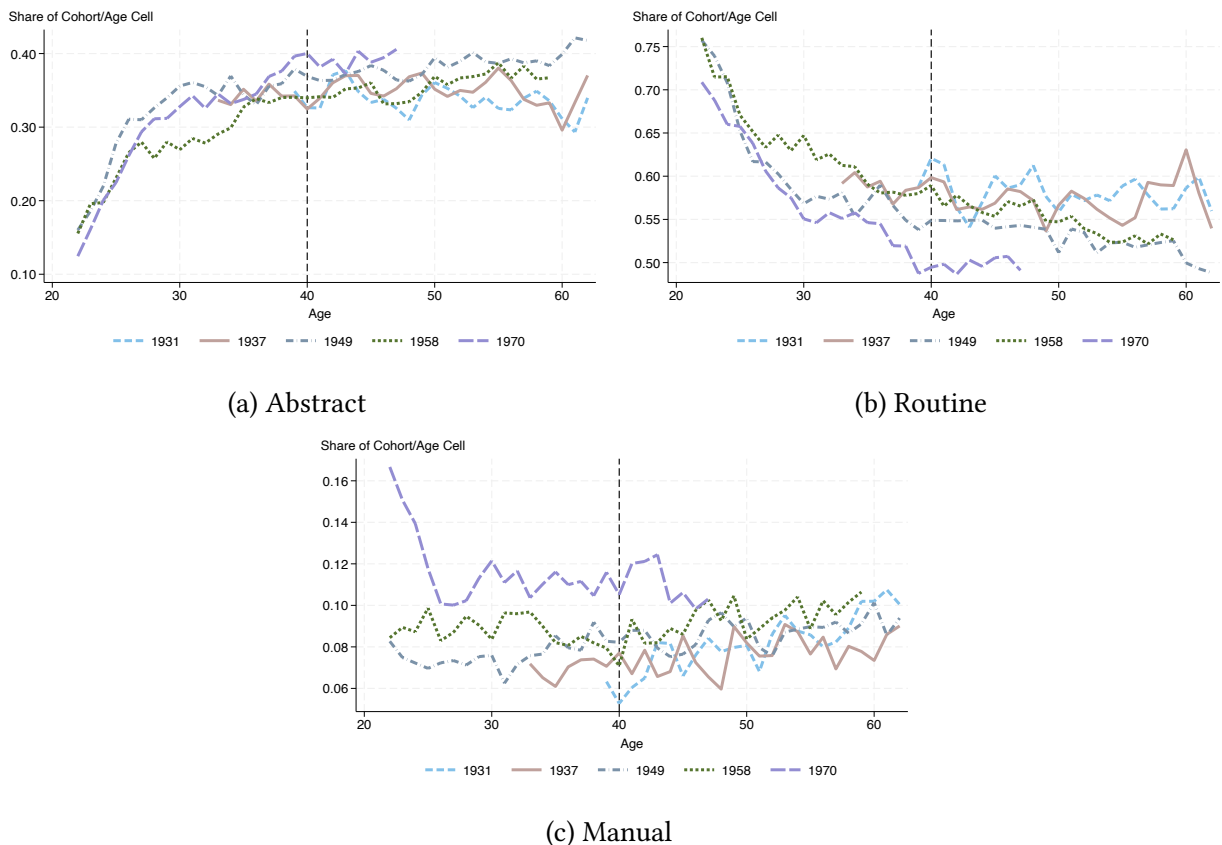


Figure E.3: Occupational Sorting by Birth Cohort

Notes: This figure summarizes the occupational composition of workers by age and birth cohort. The sample includes full-time, full-year male wage and salary workers aged 30–64 years in the MCPS 1971–2023.

F Flat Spot Identification

To determine the flat spot for workers in different occupations, I leverage differences in educational composition. The educational composition in routine and manual occupations is more diverse than in abstract occupations. High school graduates represent more than 40% of workers in routine occupations, and their share has been relatively stable over time. The share of high school graduates is also stable for manual occupations, which has a higher share of high school dropouts and a higher share of workers with some college compared to routine occupations. Workers with some college or even with a college degree have been increasingly substituting for high school dropouts in both routine and manual occupations.

Figure F.1 shows that the average level of schooling has steadily increased in abstract,

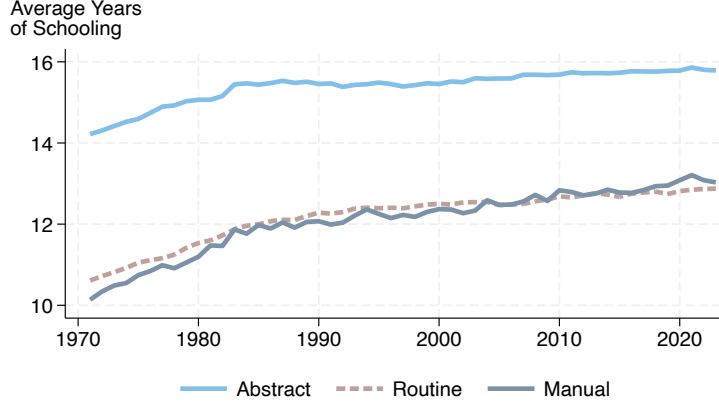


Figure F.1: The Growth of Average Schooling in Occupations

Notes: This figure summarizes the evolution of the average years of schooling in occupations. The sample includes full-time, full-year male wage and salary workers aged 30–64 years in the MCPS 1971–2023.

routine, and manual occupations during the observed period. This upward trend is nearly parallel across occupations, with workers in abstract occupations consistently exceeding routine and manual workers by approximately three years of schooling. The average level of schooling from 1971 to 2023 slightly exceeds 12 years for both manual and routine workers. Therefore, the flat spot range is set to ages 46 to 55 for both manual and routine occupations, similar to the flat spot range of high school graduates in Bowlus and Robinson (2012).

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

To set the flat spot for abstract occupations, I exploit the changes between cohorts in the share of abstract workers and the implications of these changes for the direction of cohort effects in the distribution of human capital (Bowlus and Robinson (2012)). For a worker of age a who belongs to a birth cohort c in his flat spot range:

$$\Delta \ln S_a^c = \ln S_a^c - \ln S_{a-1}^c = 0. \quad (1)$$

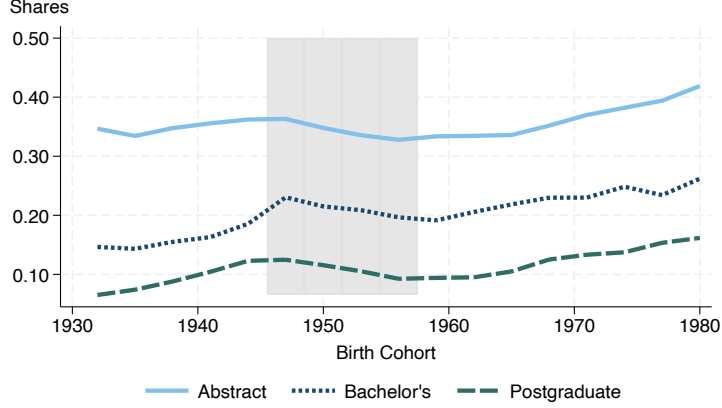


Figure F.2: Share of Workers Aged 35–40 Employed in Abstract Occupations, Holding a Bachelor’s Degree, or a Postgraduate Degree, by Birth Cohort.

Notes: This figure shows the share of workers aged 35–40 in the MCPS who are employed in abstract occupations, hold a bachelor’s degree, or have a postgraduate degree, by birth cohort. The sample includes full-time, full-year male wage and salary workers in the MCPS 1971–2023.

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:

$$\ln w_a^c - \ln w_{a-1}^{c+1} = \ln S_a^c - \ln S_{a-1}^{c+1}. \quad (2)$$

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:

$$\ln w_a^c - \ln w_{a-1}^{c+1} = \Delta \ln S_a^c = \Delta \ln S_a^{c+1}. \quad (3)$$

There are two potential sources of cohort effects for the group of highest-skilled workers: ability selection effects and changes in human capital production. If the initial ability distribution of the population is stable, an increase in the share of workers selecting into the highest-skill group implies a lower ability level for the marginal worker entering this group. Therefore, the

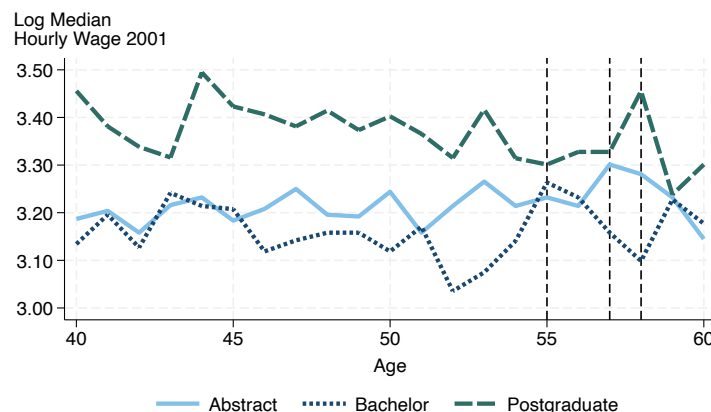


Figure F.3: Log Median Hourly Wage Profile in 2001, by Age

Notes: This figure plots the log median hourly wage for workers in the MCPS 2001 who are employed in abstract occupations, hold a bachelor's degree, or have a postgraduate degree, by age. The sample includes full-time, full-year male wage and salary workers in the MCPS 1971–2023.

ability selection effect from the expansion of the highest-skill group results in a decline in the average ability of both this group and the lower-skilled groups. Improvements in the human capital production function enable workers to accumulate human capital at a higher rate, given their initial ability level, resulting in an increase in the average human capital stock.

In the job task literature, abstract workers are regarded as the highest-skill group. Abstract occupations consist primarily of college-educated workers, while high school graduates dominate other occupations. Workers switching from routine and manual to abstract occupations are more likely to transfer from the higher-wage deciles in their occupational group to lower-wage deciles in abstract occupations. The probability of switching to abstract jobs is increasing in workers' ability (Cortes, 2016). Therefore, a rising share of the abstract occupations within a given birth cohort implies that more workers in this cohort are transferring from lower-skill occupations, introducing a negative selection bias.

Figure F.2 plots the share of FTFY workers aged 35 to 40 years in the MCPS who were employed in abstract occupations, who had a bachelor's degree, and who had a postgraduate degree.¹⁸ The share of workers in abstract occupations in their late 30s is declining for cohorts born from 1947 to 1956, following a trajectory similar to that of workers with postgraduate and

¹⁸Workers aged 35 to 40 are approaching their potential flat spot age range.

bachelor's degrees. This change is likely to be driven by shifts in the population's educational composition rather than demand-driven changes in the labor market.

In 2001, the 1947 birth cohort reached age 54, and the 1956 birth cohort reached age 45. Since cohorts born between 1947 and 1956 experienced declining shares of college graduates and workers employed in abstract occupations, the ability selection effect is positive. As the average level of schooling in abstract occupations increased during the observed period, workers also likely benefited from positive changes in human capital production functions. Thus, the aggregate cohort effect for abstract workers born between 1947 and 1956 should be positive. This means that in 2001, the wage growth observed for workers from these cohorts underestimates life-cycle human capital growth:

$$\ln w_a^c - \ln w_{a-1}^{c+1} < \Delta \ln S_a. \quad (4)$$

If the cohort effect for workers in abstract occupations born between 1947 and 1956 was positive, the life cycle cross-sectional profile of earnings in 2001 reached its peak at an earlier age compared to the human capital profile. Figure F.3 plots the life cycle wage profile for workers in abstract occupations, workers with bachelor's degrees, and with postgraduate degrees in 2001. For workers with bachelor's degrees, the wage profile peaked at 55. For workers with post-graduate degrees, the profile peaked three years later at 58. Finally, for workers in abstract occupations the profile peaked at 57, reflecting the mixed educational composition of the group. For workers aged 57, the cohort effect still caused the wage change to underestimate the change in human capital stock. Therefore, the life-cycle human capital profile of abstract workers cannot peak earlier than age 57.

Based on the educational composition of workers in abstract occupations and cross-sectional evidence, the flat spot age range for abstract workers is set at 51–60. It begins one year later than the flat spot region for workers with college degrees in Bowlus and Robinson (2012). The sensitivity analysis performed in Appendix H shows that shifting the flat spot region for abstract workers to later or earlier ages has a modest effect on price estimates.

G Sensitivity of Price Estimation to Occupational Switching

To assess whether occupational switching behavior significantly alters my results, I estimate the price series for workers who remained in the same occupational group throughout their participation in the MORG survey. Figure G.1 illustrates the price series estimated for both restricted and unrestricted samples. The unrestricted samples include full-time wage or salaried workers in MORG during month eight of the CPS and FTFY workers in the MCPS sample. The restricted sample includes full-time wage and salaried workers in MORG who stayed in the same occupational group over the year.

In 1985 and 1995 the CPS changed its housing unit numbering schemes, preventing matching across some individuals between 1984–1985, 1985–1986, 1994–1995, and 1995–1996. Therefore, I estimate the evolution of occupational human capital prices from 1987 to 1994 and from 1997 to 2017, when occupation stayers can be identified in the MORG sample.

The trends in human capital prices are similar for both occupational group stayers and unrestricted samples across all occupations. This implies that occupational switching has a limited effect on the price estimation results. Price series exhibit a price decline from 1987 to 1994 for all occupations and all samples, although the estimated decline in price is lower for the MCPS sample. Since the late 1990s, prices for routine and manual occupations have been decreasing at a smaller rate compared to the late 1980s and early 1990s. Moreover, prices for abstract occupations have been slowly increasing in all samples.

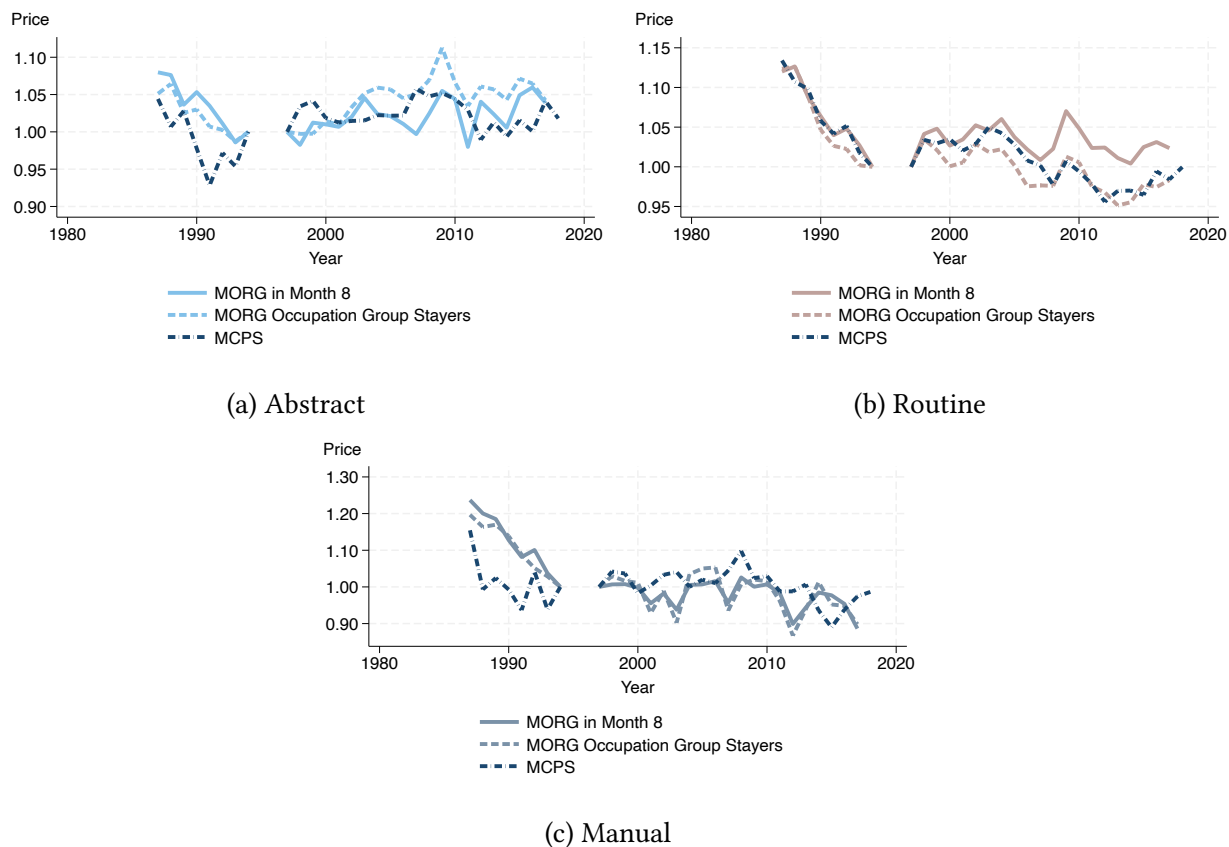


Figure G.1: Sensitivity of Price Series to the Occupational Switching

Notes: This figure plots the estimated baseline price series alongside price series for full-time workers in MORG (based on wage data from month 8) and full-time occupation stayers in MORG (based on wage data from month 8).

H Sensitivity to Changing the Flat Spot Age Range

This section examines the sensitivity of price series estimates to the choice of the flat spot region. Panel (a) of Figure H.1 shows that starting the flat spot at age 51 or 53 produces similar price series for abstract occupations. However, choosing an earlier flat spot leads to even higher estimated prices compared to the baseline result. This is particularly true for the period after 1990 when the share of high school graduates and high school dropouts employed in abstract occupations reached a plateau (see Figure 2). A potential explanation is that around this period, abstract occupations became dominated by highly educated workers, who still experience the growth of human capital in their late 40s. 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 depreciation rates of cognitive skills in senior workers.

The price series for routine occupations align with the expected pattern, with early flat spots leading to the overestimation of the price series, and late flat spots resulting in the underestimation, as they potentially capture the effect of human capital depreciation and retirement. The price series for manual occupations are relatively insensitive to shifting the flat spot range, with no persistent gaps between price estimates that are based on different flat spot age ranges.

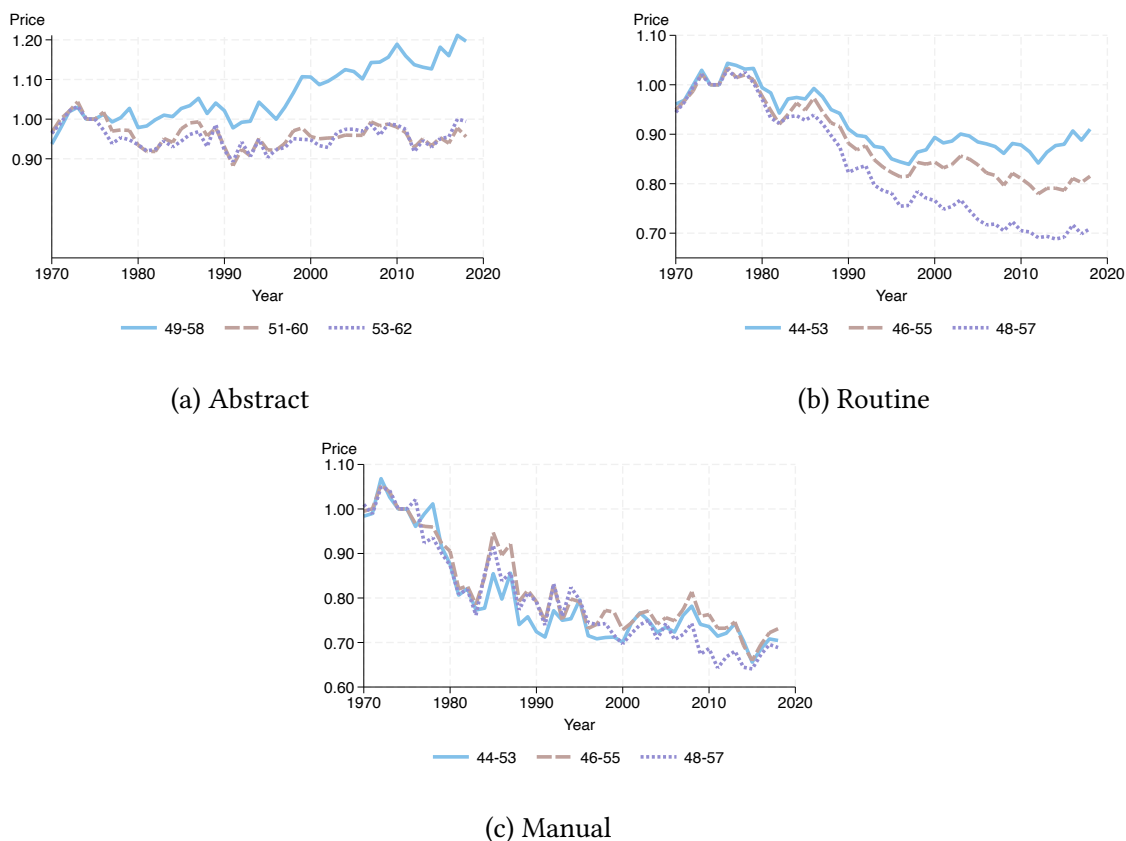


Figure H.1: Sensitivity of Price Series to Changing the Flat Spot Age Range

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 male wage and salary workers in the MCPS 1971–2023.

I Sensitivity to Wage Measure

Using median hourly wages in the estimation allows me to avoid the issue of inconsistent top-coding of income values in the CPS. However, it is common in the labor economics literature to rely on average wages and average log wages in the analysis. This section shows that my findings are robust to the use of alternative wage measures. Figure I.1 compares the price series estimated using the median hourly wages, average hourly wages, and average log hourly wages. The increase in the price for abstract occupations 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 for routine occupations is lower in magnitude for the average wages than for the median wages. However, the direction of the change is preserved.

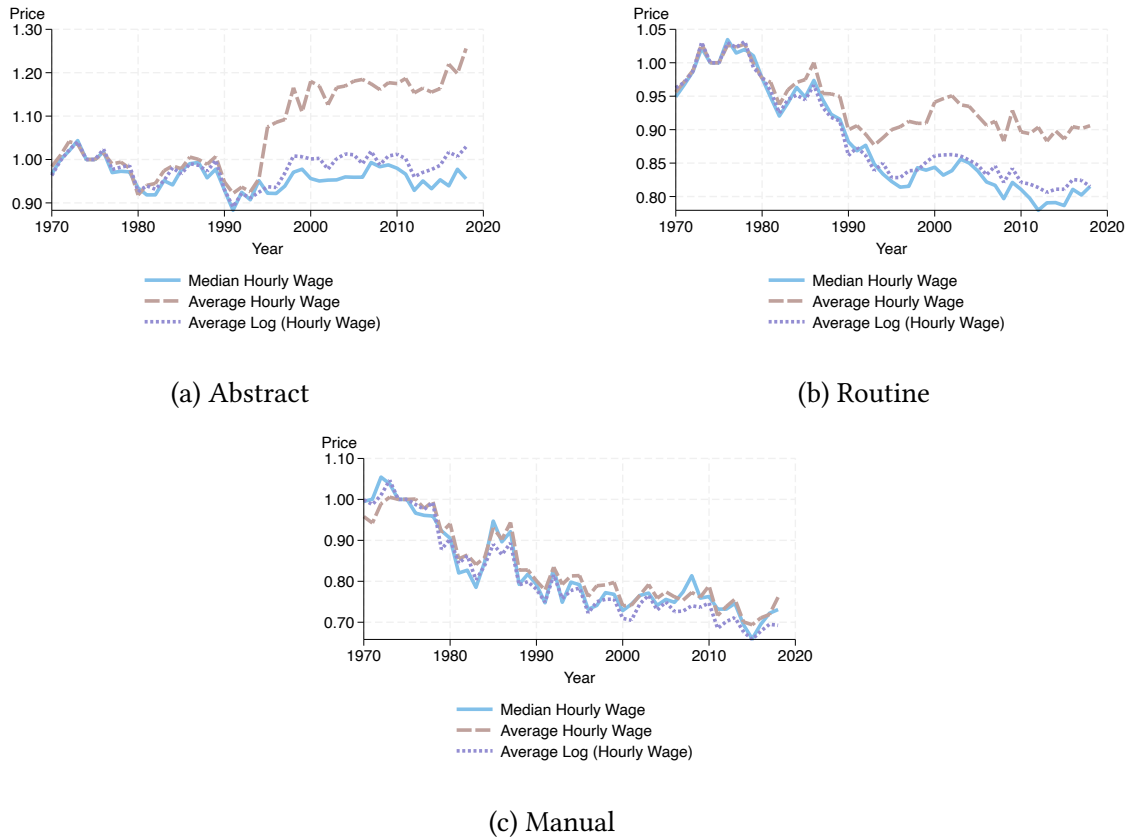


Figure I.1: Sensitivity of Price Series to Using Alternative Wage Measures

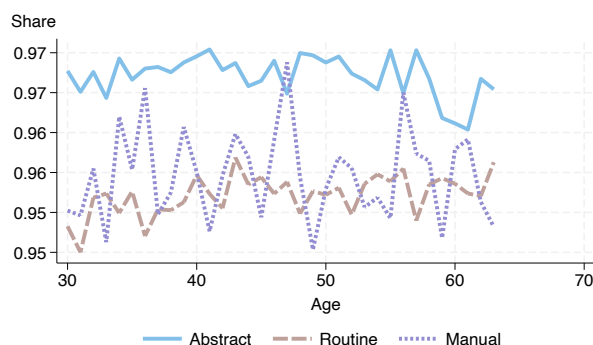
Notes: This figure displays the evolution of estimated prices of human capital using average wage, median wage, and log wage to compute the price series. The sample includes full-time, full-year male wage and salary workers in their flat spot age ranges in the MCPS 1971–2023.

J Differences in Contracts Across Occupations

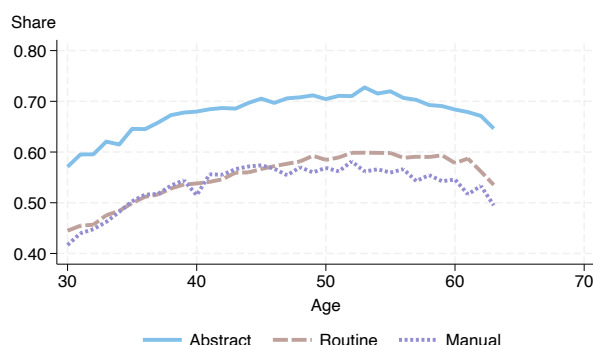
The MCPS survey asks respondents whether their employer or union paid for all or part of the cost of premiums for an employment-based group health insurance plan that the respondent was included in the last year. Panel a) of Figure J.1 summarized the life-cycle profile for the average share of workers who report that their employer or union paid for all or part of costs for the employment-based group health insurance plan. Since almost 95% of workers had access to the group health plan, differences in compensation driven by the health plan coverage are likely to be small.

Panel b) of Figure J.1 summarized the life-cycle profile for the average share of workers who were included in pension plan at work. Abstract workers were more likely to be included in

a pension plan. It is possible that employers have to compensate workers in routine and manual occupations 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) Group Health Plan



(b) Pension Plan

Figure J.1: Share of Workers with Employer-sponsored Pension and Group Health Plans by Age

Notes: This figure summarized the average share of workers who report having access to employer-sponsored group health plans or pension plans by age. The sample includes full-time, full-year male wage and salary workers in their flat spot age ranges in the MCPS 1980–2023.

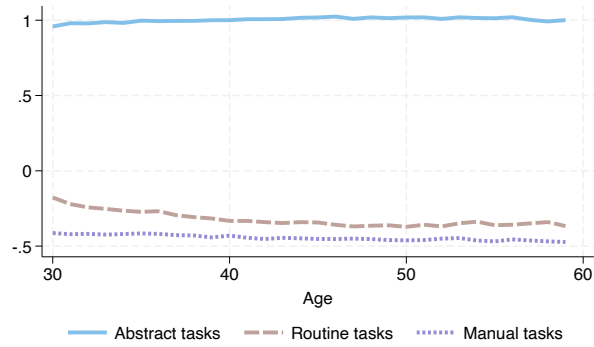
K Differences in Job Tasks Across Occupations

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 Beaudry et al., 2016, Cortes, 2016, Böhm, 2020, and Cavaglia and Etheridge, 2020), 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

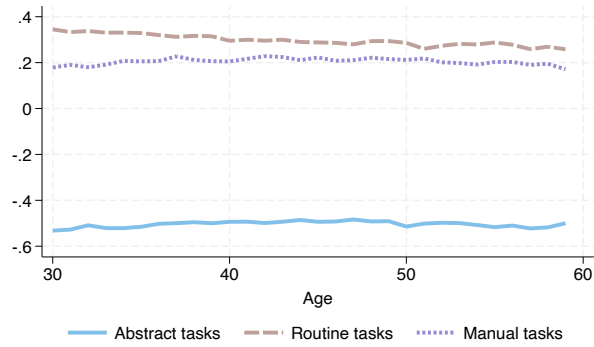
task intensity.

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 workers' 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" scores. The measure of routine task intensity is the average of "adaptability to work requiring set limits, tolerances, or standards" and "finger dexterity" scores. The measure of manual task intensity is the "eye, hand, and foot coordination" score. I standardize all task intensity measures to have a zero mean and a standard deviation equal to one.

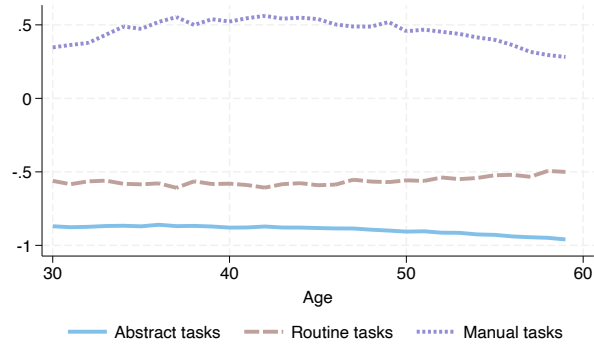
Figure K.1 shows the evolution of the average task intensity for all cohorts of workers by age. The average intensity of abstract tasks exceeds the average intensities of routine and manual tasks for workers in the abstract occupational group. Moreover, the intensity of abstract tasks remains stable over the worker's age, implying that comparable occupational tasks, as measured at the occupation level, are assigned to workers of different ages. The average intensity of routine tasks is the highest in routine occupations compared to other occupations. 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 manual tasks exhibits a slight bell-curve shape, the average manual task intensity remains relatively stable for workers in their flat spot age 46–51.



(a) Abstract



(b) Routine



(c) Manual

Figure K.1: Average Task Intensity in Occupational Group by Age

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

L Educational Composition within Abstract Occupations

Figure L.1 explores the evolution of educational composition of managers and professionals between 1970 and 2022. Professional occupations became dominated by workers with postgraduate degrees beginning in the early 1970s, and the share of workers with postgraduate degrees has consistently exceeded 40%, compared to 10% to 25% for managerial occupations. 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.

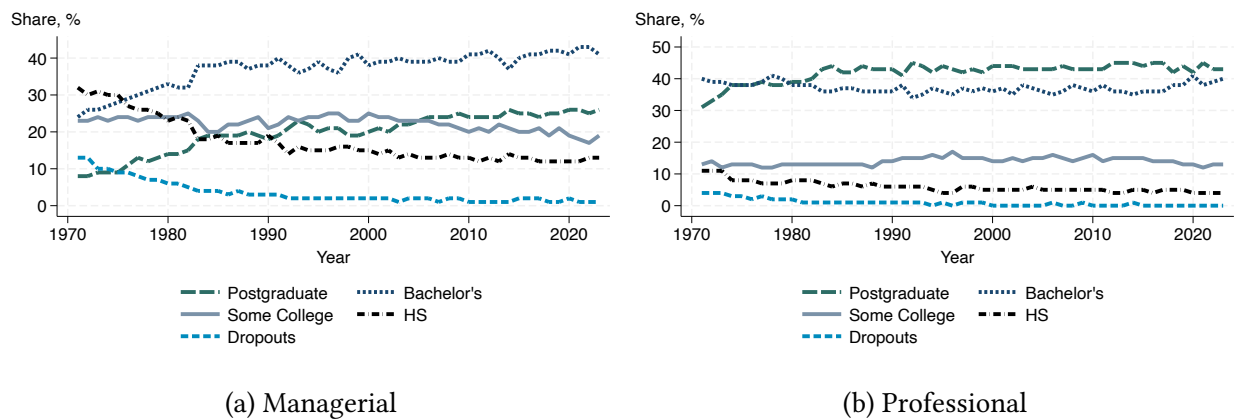


Figure L.1: Educational Composition within Abstract Occupations

Notes: This figure summarizes the educational composition of workers in managerial and professional occupations. The sample includes full-time, full-year male wage and salary workers aged 30–64 years in the abstract occupational group in the MCPS 1971–2023.