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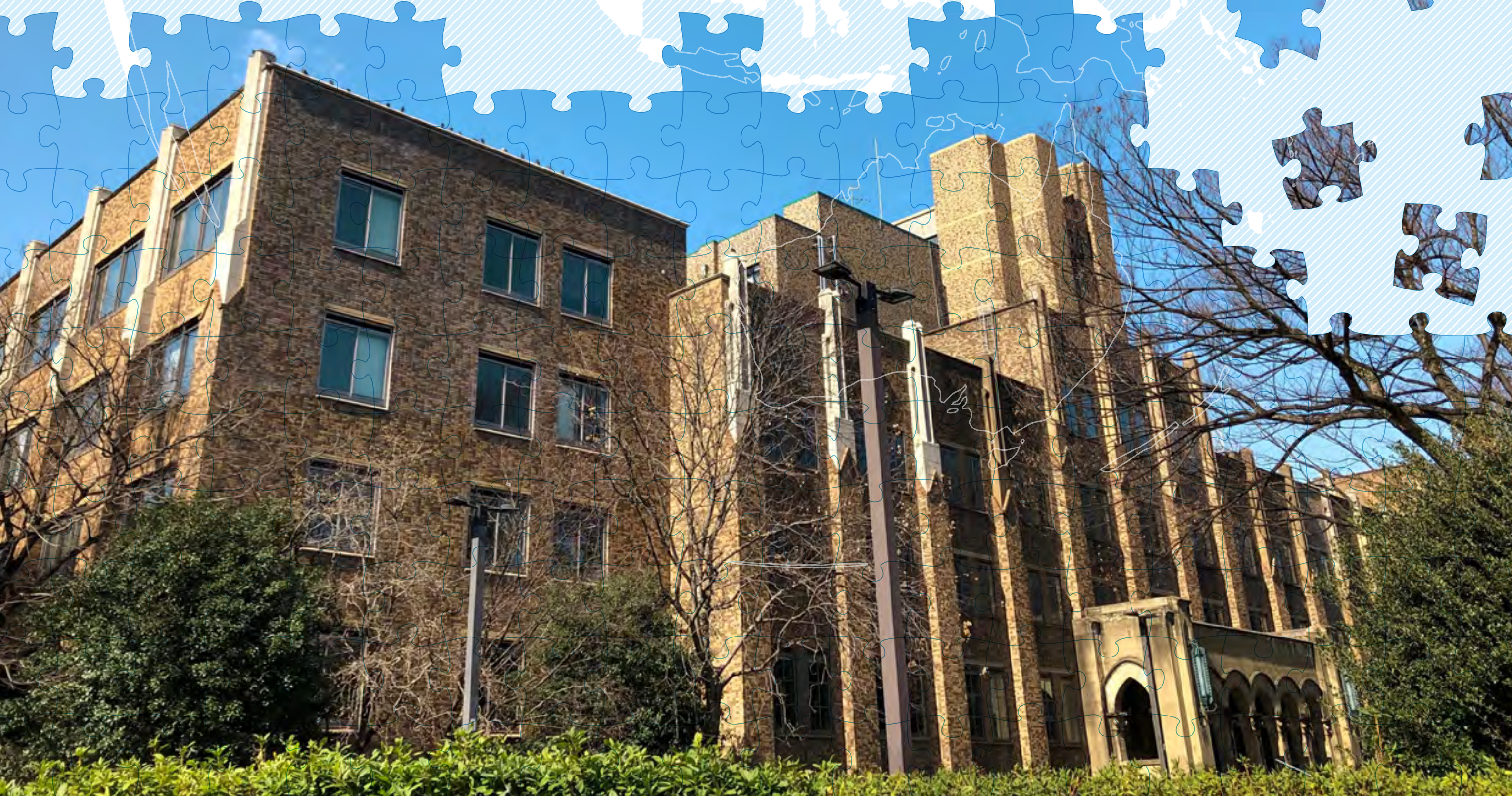
Later-life Careers as a Volatile and Equalizing Trajectory: A Long-term Perspective on Analytical Skill Usage across the Life Course in Japan



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Later-life Careers as a Volatile and Equalizing Trajectory:

A Long-term Perspective on Analytical Skill Usage across the Life Course in Japan

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Studies on the life course process of labor market inequality have shown that occupational status diverges early in one's career and remains stable in the midlife period; however, the long-term trajectory of one's career, including the pensionable age, is still unclear. Using retrospective data matching with occupational information networks in Japan, I describe how analytical skill usage, which is a detailed component of class mobility, changes or remains stable from 20 to 69 years of age. I find that careers are more volatile in later life and that volatility appears as a decrease in skill level. Men who enjoy greater opportunities for training and promotion within a firm experience a significant decrease in analytical skill usage compared with women. The educational difference in analytical skill usage is persistent in later life, implying that general human capital has a durable benefit in later life. The results highlight that the divergent pathways in one's early career do not necessarily continue in later life. Rather, the advantage acquired in one's early career can be lost later in life, especially for men.

Keywords: Career, Occupational volatility, Analytical skill, Japan

Acknowledgments

A replication package is available at https://github.com/sittaningo/replication/tree/main/skilltraj. When the paper is accepted for publication, the replication package in github will be archived on Dataverse. I thank the 2015 SSM Survey Management Committee for allowing me to use the SSM2015 data. This paper was presented at the "Secondary Data Analysis about Social Stratification and Social Mobility" meeting; participants of the Japanese Association of Mathematical Sociology 74th Conference provided helpful feedback. I thank Ryota Mugiyama for his advice on this paper.

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Introduction

Most countries are experiencing rapid population aging, leading policymakers to increasingly focus on retaining older workers in the labor market. The policy approach has shifted from promoting early retirement to extending the work-life period in European countries, although early retirement practices persist in some countries (Wise 2010). As working lives extend, there is a growing interest in how occupations change or remain stable in later life. Investigating this agenda offers new insights into postmidlife careers, which have traditionally been viewed as settled (Gathmann and Schönberg 2010).

Previous studies have shown that occupational status diverges early in one's career and stabilizes during the midlife period (A. Manzoni, Harkonen, and Mayer 2014; Struffolino 2019; Winkle and Fasang 2020; Doren and Lin 2019; Lersch, Schulz, and Leckie 2020; Tomaskovic-Devey, Thomas, and Johnson 2005; Lu, Wang, and Han 2017). However, few scholars have considered the long-term career trajectory to extend to the pensionable age. Later-life careers can be a significant source of occupational volatility, potentially equalizing occupational inequality as workers face mandatory retirement, ageism, and functional limitations (Visser et al. 2016; Radl 2013; Higo and Klassen 2015; Carlsson and Eriksson 2019; Corna 2013). By describing how occupations change or remain stable in later life, I complement previous research by providing insight into the age at which early-career occupational positions persist.

To understand the long-term dynamics of occupational positions, occupational skills can serve as the underlying link between occupations that extend beyond class categories throughout the life course (Villarreal 2019; Cheng and Park 2020). Workers acquire occupation-specific human capital over their careers (Jonsson et al. 2009; Sullivan 2010; Gathmann and Schönberg 2010). They often move to new occupations to utilize their occupation-specific human capital (Mouw, Kalleberg, and Schultz 2024). Some studies have suggested that this mobility continues throughout individuals' careers (Bihagen, Shahbazian, and Kjellsson 2024), while others indicate stability in the postmidlife period (Gathmann and Schönberg 2010). As occupational tenure increases, the costs of occupational mobility also increase because workers take away the human capital they have built (Gathmann and Schönberg 2010). Consequently, workers tend to move to new occupations with similar skill requirements (Sullivan 2010; Gathmann and Schönberg 2010). Occupational skills potentially link occupational mobility with changes in occupational prestige and wages over the life course.

Additionally, I examine sociodemographic differences in long-term occupational skill trajectories. Gender and education can lead to different career paths (Cheng 2014; Damaske and Frech 2016; Winkle and Fasang 2020; Doren and Lin 2019) [1], and this trend continues into later life. For example, men are typically expected to work full-time consistently, whereas women are more likely to have interrupted careers and reenter the workforce part-time to balance work and family responsibilities (Damaske and Frech 2016; Doren and Lin 2019). Higher education is correlated with not only greater cognitive ability (Tomaskovic-Devey, Thomas, and Johnson 2005) but also greater signal ability and work ethic to employers (Spence 1973). Gender and education distinctly shape occupational pathways later in life, intersecting with institutional arrangements in the Japanese labor market.

I contribute to the literature by demonstrating that later-life careers are an alternative source of occupational volatility rather than a mere continuum from the midlife period (Gathmann and Schönberg 2010; D. Autor and Dorn 2009; Jarvis and Song 2017). Workers, irrespective of gender and educational background, are allocated to occupations with less analytical skill usage later in life. This decline is particularly notable for men, who typically enjoy stable employment and training opportunities before age 60 but face mandatory retirement and subsequent re-employment with lower wages (Higo and Klassen 2015). This suggests that scholars should not regard later life merely as a residual phase in which one waits for retirement but rather as a dynamic stage where one's occupational skill allocation changes.

Theoretical Background

Long-term Occupational Trajectory over the Life Course

Previous studies have shown that one's occupational position is shaped early in one's career (A. Manzoni, Harkonen, and Mayer 2014; Struffolino 2019; Winkle and Fasang 2020; Doren and Lin 2019; Lersch, Schulz, and Leckie 2020; Tomaskovic-Devey, Thomas, and Johnson 2005; Lu, Wang, and Han 2017). For example, A. Manzoni, Harkonen, and Mayer (2014) demonstrated that occupational prestige increases for up to 15 years for men and 9 years for women after entering the labor market. Struffolino (2019) identified eight clusters of early career paths and examined their relationships with gender and education. Lersch, Schulz, and Leckie (2020) revealed a divergence in occupational prestige for up to 180 months. These studies confirm the cumulative (dis)advantage theory (DiPrete and Eirich 2006; Ferraro, Shippee, and Schafer 2008), which posits that advantages acquired early in life accumulate over the life course.

Occupational inequality that emerges early in one's career tends to stabilize during the midlife period. Gathmann and Schönberg (2010) showed that the rate of occupational mobility declines as workers age. In the midlife period, the cost of occupational mobility

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[1] Another important factor for career trajectories is race/ethnicity (Damaske and Frech 2016; Winkle and Fasang 2020; Doren and Lin 2019). However, given that approximately 98% of Japan's population is Japanese (Korekawa 2018), there is minimal variation in this regard.

increases because workers need to (at least partially) forgo their occupation-specific human capital (Neal 1999). Moreover, the return on occupational mobility decreases because middle-aged workers have less time to invest in a new occupation (Jarvis and Song 2017). As the labor market transforms, the demand for occupations in which middle- and older-aged workers engage decreases, leading them to remain in occupations with longer tenure (D. Autor and Dorn 2009). A recent study by Bihagen, Shahbazian, and Kjellsson (2024) suggested that occupational prestige continues to improve after midlife, except for in the 1925–1934 birth cohort. While the evidence is not consistent, at least the pace of growing one's occupational prestige is slower in the midlife period than in one's early career.

This study's central argument is that such stability does not persist into later life. Occupational changes increase again later in life due to mandatory or gradual retirement, senescence, and ageism. The likelihood of retirement depends on the occupations workers have engaged in before their retirement (Visser et al. 2016; Radl 2013). Before retirement, workers often move to occupations with lower status and fewer working hours (Visser et al. 2018; Cahill and Quinn 2020; Carr et al. 2021). Senescence leads older workers to gradually retire, as they can no longer engage in full-time work. Ageism restricts access to higher-status and prestigious occupations, as employers perceive older applicants as being inflexible, slow, disorganized, difficult, and expensive to train (Roscigno et al. 2007; Carlsson and Eriksson 2019). This study investigates how these changes contribute to increased occupational volatility later in life, particularly in terms of occupational downgrading.

This occupational volatility in later life is hypothesized to equalize occupational inequality. The age-as-leveler (AAL) hypothesis (Corna 2013) suggests that (dis)advantages converge over time. For instance, people universally experience senescence, which narrows the gaps in gender and education. Although the AAL hypothesis is often used to explain the convergence of health inequality in later life (Corna 2013), it can also explain the convergence of occupational inequality. As argued, occupational skills decline later in life due to mandatory retirement (Higo and Klassen 2015), senescence, and ageism (Roscigno et al. 2007; Carlsson and Eriksson 2019).

In Japan, the AAL hypothesis can also be observed in later life. Mandatory retirement and re-employment systems have been introduced as policy. The re-employment system, which was established under the Elderly Employment Stabilization Law, provides continuous employment with lower wages until the pension eligibility age (Kondo and Shigeoka 2017; Higo and Klassen 2015). Such institutional arrangements are expected to reduce one's analytical skill usage, especially among men and those with higher education. Compared to their counterparts, these groups benefit from stable employment and training opportunities in their early to middle careers, similar to in other OECD countries. However, mandatory retirement and re-employment systems result in a decrease in skill levels around the pensionable age.

The Role of Occupational Skill in Labor Market Inequality

Occupational skill is defined as "technical task requirements that are necessary for effective performance of jobs" (Handel 2020, 4). In this view, such skills is an occupational characteristic rather than an individual characteristic (i.e., human capital). Individual-based skills and occupation-based skills are closely correlated (D. H. Autor and Handel 2013). According to occupational internal labor market theory (Mouw, Kalleberg, and Schultz 2024), workers build up their occupation-specific human capital (skills) in their career, and they move to occupations with higher occupational skill requirements to use their (grown) human capital to increase their pay. While I describe the change in occupational skill requirements in an occupation, that change is closely associated with human capital.

Occupational skills can provide a plausible explanation for why class and prestige increase over the life course. Recent scholars have revealed through social network analyses that the labor market is segmented by occupational skills rather than traditional social class schema (e.g., Cheng and Song 2019; Villarreal 2019; Lin and Hung 2022). This is intuitive in terms of occupation-specific human capital theory. According to this theory, work experience in an occupation is highly occupation-specific (Gathmann and Schönberg 2010; Sullivan 2010), and such work experience is transferrable only to occupations with similar skill sets. As argued, the concept of an occupational internal labor market (Mouw, Kalleberg, and Schultz 2024) suggests that workers move to occupations with higher classes and wages as they accumulate occupation-specific human capital. I directly investigate occupational skill allocation over the life course, contributing to previous studies that focused on class and prestige (e.g., Bihagen, Shahbazian, and Kjellsson 2024; Lersch, Schulz, and Leckie 2020).

Theoretically, occupational skill requirements grow over the life course as workers accumulate occupation-specific human capital. Contextual factors, however, can modify this trajectory. For example, routine-biased technological change decreases the prevalence of occupations with more intense routine tasks. Older workers, who are more likely to engage in occupations with more routine tasks, may stay in these occupations because the cost of new occupational investment increases (D. Autor and Dorn 2009). In Japan, mandatory retirement and re-employment systems (Higo and Klassen 2015) are supposed to decrease skill levels after 60 years of age. Thus, one's skill level in later life is modified by institutional arrangements.

In this study, I use analytical skill because it is a higher-order and generalized cognitive skill applicable across various industries and occupations (Liu and Grusky 2013; Horowitz and Ramaj 2023; Adserà, Ferrer, and Hernanz 2023). The number of occupations requiring higher levels of analytical skill and the returns on them have increased over time (Liu and Grusky 2013). Analytical skill gauges career jobs and is positively correlated with wages (Adserà, Ferrer, and Hernanz 2023). As a human capital acquired in career jobs, analytical skill is suitable for observing occupational skill trajectories over the life course.

Japan as the Most Aged Society

Japan is highlighted as a rapidly aging society. In 1950, the proportion of individuals aged 65 or older in the entire population was 4.9% (National, Institute of Population and Social Security Research 2023). By 2020, this proportion had increased to 28.6% (National, Institute of Population and Social Security Research 2023). The pace of population aging is also rapid; it took only 24 years for Japan's proportion of individuals aged 65 or older to increase from 7% to 14%. This rapid aging is partly due to an increase in life expectancy. According to the WHO, the average life expectancy in Japan is the highest in the world. In 2022, the average life expectancy in Japan was 84.3 years. Consequently, the labor force participation of older people (aged 65 or older) in 2022 was 25.6% in Japan, which was the third highest among OECD countries (OECD 2020). In sum, Japan is the most aged society in terms of both health and working lives. Other countries, including those in East Asia, Europe, and the United States, will experience similar changes, i.e., further population aging, greater life expectancy, and greater labor force participation of older people. Thus, investigating how careers in later life are shaped in Japan can provide a glimpse into the future for other countries.

Data and Methods

Data and Analytical Samples

I use the data from the Social Stratification and Mobility Survey conducted in 2015 (SSM2015). The SSM2015 is a nationally representative survey that collected information from participants aged 20 to 79 through a stratified two-stage random sampling method. The SSM2015 has two strengths related to addressing the research question in this study. First, the SSM2015 asked respondents retrospectively about their annual occupations ranging from their first job to their current job. This detailed career information allows for the illustration of a long-term occupational trajectory. Second, the SSM2015 includes 3-digit occupation codes, which enables matching to the Occupational Information Network in Japan (O-NETJ), which I introduce below. By matching the 3-digit occupations in SSM2015 with those in O-NETJ, it is possible to estimate the analytical skill each occupation requires.

The second data source is the Occupational Information Network in Japan (O-NETJ, version 3.0.0), which is the Japanese version of the Occupational Information Network in the USA (O*NET). The O-NETJ collects information about the skills required for various occupations. This information is gathered from incumbents in the O-NETJ. I match occupations in the SSM2015 with those in the O-NETJ following the procedure outlined by Mugiyama and Tagami (2024). In this process, teachers (no information about the school type), product manufacturing workers (no information about the product), company employees, self-employed workers (no information about the occupation), former military personnel, and former landlords are excluded. After matching the occupations, I standardize each component of the analytical skill in the O-NETJ at the person-year level. I then sum the standardized components to construct the analytical skill usage for each occupation and standardize the analytical skill usage again at the person-year level.

The original sample of the SSM2015 consists of 7,817 individuals. To observe the occupational skill trajectory from ages 20 to 69, I restrict the sample to those aged 70 to 79, resulting in 1,485 individuals. I observe the occupational skill trajectory of older respondents aged 20 to 69 years (74250 person-year observations). I exclude cases where occupations cannot be matched, individuals are out of the workforce (24,202 observations), there is no information about gender (14 observations), or there is no information about education (264 observations). I also exclude occupational careers before 1956 because GDP and unemployment rate data are available only from 1956 onward (51 observations). The final sample size totals 49,804 observations.

Measures

The primary measurement in this study is the analytical skill usage in an occupation. To construct this model, I follow the procedure of Liu and Grusky (2013). I select four components from the O-NETJ: active learning, critical thinking, learning strategies, and complex problem solving. These components are chosen because the O-NETJ does not collect ability data. Instead of conducting confirmatory factor analysis, I simply add the items from the O-NETJ. Each item is standardized at the person-year level. The top- and bottom-ranked occupations in terms of analytical skill are presented in Table 1.

Table 1: Top and Bottom Occupation in Analytical Skill

Occupation	Score
Researchers In Natural Science	3.53
Business Management Consultants	3.02
Other Legal Professionals	2.98
High School Teachers	2.32
Elementary School Teachers	2.15
Supermarket And Other Shop Cashiers	-1.67
Transportation Laborers	-1.97
Miscellaneous Laborers	-2.04
Other Technical Workers/Production Process Workers	-2.18
Computer And Other Similar Equipment Operators	-2.31

Note: Data are from the SSM2015 matched to data from the O-NETJ. Own calculation. The score represents the standardized analytical skill usage in each occupation. The detailed procedure for calculating the score is shown in Section 2.2. The top five occupations have the highest values for analytical skill usage, and the bottom five occupations have the lowest values.

For sociodemographic variables, I use gender, age, and education. In the SSM2015, six levels of education are measured: junior high school, senior high school, professional training college, junior college, college or university, and graduate school. Professional training colleges, junior colleges, colleges or universities, and graduate schools are assigned to higher education.

To avoid the age-period-cohort identification problem, I adjust for period effects using the unemployment rate and GDP growth for each year, following Kratz and Brüderl (2021). I use statistics from the Labor Force Survey for the unemployment rate and from the System of National Accounts for GDP Growth. These measures are incorporated into the SSM2015 for each period. The mean, standard deviation, and percentage of each measure are shown in Table 2.

Table 2: Descriptive Statistics

		N	Percent	Mean	SD
	Analytical Skill Usage	49804		0.00	1.00
	Age	49804		43.20	13.49
Gender	Male	29248	58.73		
	Female	20556	41.27		
Education	Low	41673	83.67		
	High	8131	16.33		
	GDP	49804		4.54	4.17
	Unemployment Rate	49804		2.56	1.20
	All	49804	100.00		

Note: Data are from the SSM2015 is matched to data from the O-NETJ. Own calculation. *N* equals the number of person-years. Continuous measures include the mean value and standard deviation. Categorical measures include the number of observations and percentage.

Data Analytic Plan

Following recent suggestions for formalized procedures in quantitative sociology (Lundberg, Johnson, and Stewart 2021; Kohler, Class, and Sawert 2023), this study explicitly outlines the data analytic plan through three components: what this study aims to estimate (estimand), what this study can estimate in a real-world setting (identification), and how this study determines the estimand (estimation). Distinguishing these procedures helps to clarify the purpose and assumptions of this study, allowing subsequent studies to answer this question (Lundberg, Johnson, and Stewart 2021).

(1) The unit-specific quantity of (2) the target population is required to build the estimand (Lundberg, Johnson, and Stewart 2021). The unit-specific quantity in this study is descriptive. This study describes the age trajectory of occupational skills rather than the effect

of age on occupational skills. I focus on those born in during the 1936–1945 period, i.e., prebaby boomers, who are suitable targets for this study for two reasons. Before prebaby boomers, people went to war, and many of those individuals died in the war, resulting in a selective sample. After prebaby boomers, long-term occupational careers remain difficult.

Directed acyclic graphs (DAGs) are often used for identification (Lundberg, Johnson, and Stewart 2021). While they are rooted in the causal inference literature (Pearl 2009), DAGs are also useful in descriptive analysis (Lundberg, Johnson, and Stewart 2021). The DAG used in this study is shown in Figure 1. To estimate the age trajectory of occupational skills, two sources of bias need to be considered. The first is the age-period-cohort confounding problem, where changes in occupational skill level are generated by social change (period) instead of solely by individual aging. The second issue is selective attrition, where women and those beyond the pensionable age tend to exit the labor market, affecting the change in occupational skill level.

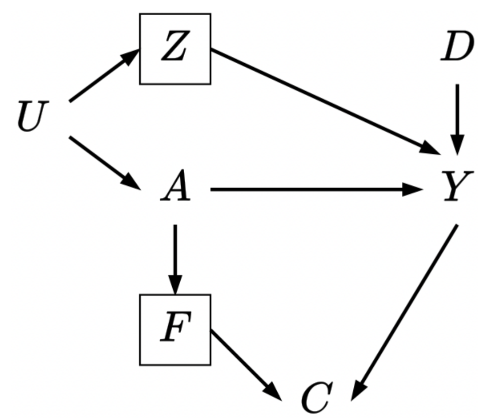


Figure 1: Directed Acyclic Graph
Note: Direct acyclic graphs show the assumption in this study. A is age, Y is analytical skill level, and D is gender and education. Z is period and A is an unobserved feature preventing the collider, which can be conditioned through fixed effect estimation. To correctly describe the age trajectory of analytical skill by gender and education, I use fixed effect estimation to block the confounding pathways from U and C by adjusting for Z and F.

To avoid these problems, I apply the fixed effects model shown in Equation 1. OSL_{it} (Y in Figure 1) is the occupational skill level of a given person i in each year t. $Age_{n,it}$ in (A in Figure 1) is measured nonparametrically with 50 dummy variables ranging from ages 20 to 69 (reference age: 25). I estimate the interaction terms of age with sociodemographic attributes (education and gender). η is the estimator this study aims to estimate. X_{it} includes confounders such as period and other time-invariant covariates.

$$OSL_{it} = \alpha_i + \Sigma_{n=20}^{69}\beta_n Age_{n,it} + \theta_{i\in Age=25}\begin{bmatrix} Edu_i \\ Sex_i \end{bmatrix} + \eta Age_{n,it}\begin{bmatrix} Edu_i \\ Sex_i \end{bmatrix} + \gamma X_{it} + \epsilon_{it} \quad (1)$$

According to Kratz and Brüderl (2021), the fixed-effect model relies on within-individual variation; thus, we do not need to assume that α_i is correlated with $Age_{n,it}$, thereby avoiding sample selection bias. Furthermore, the fixed effects model eliminates cohort confounding. By adding the unemployment rate and GDP growth in each year as a proxy for the period confounding into the models, I can obtain the estimator for the age trajectory of analytical skill.

I drop missing values at the case level; thus, the data are unbalanced. Cluster-robust standard errors are applied to the model.

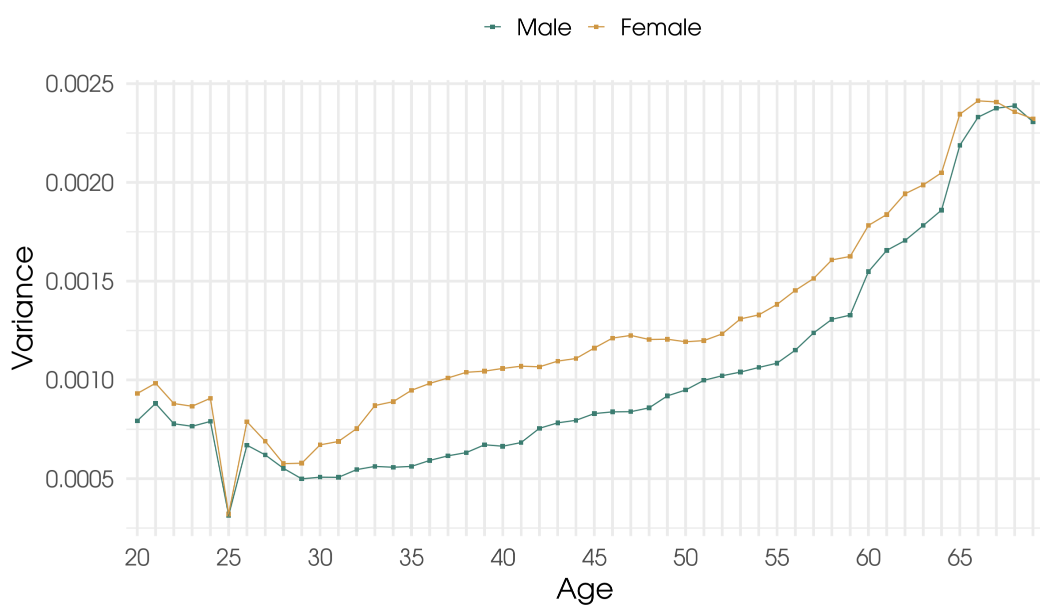
Results

Occupational Volatility over the Life Course

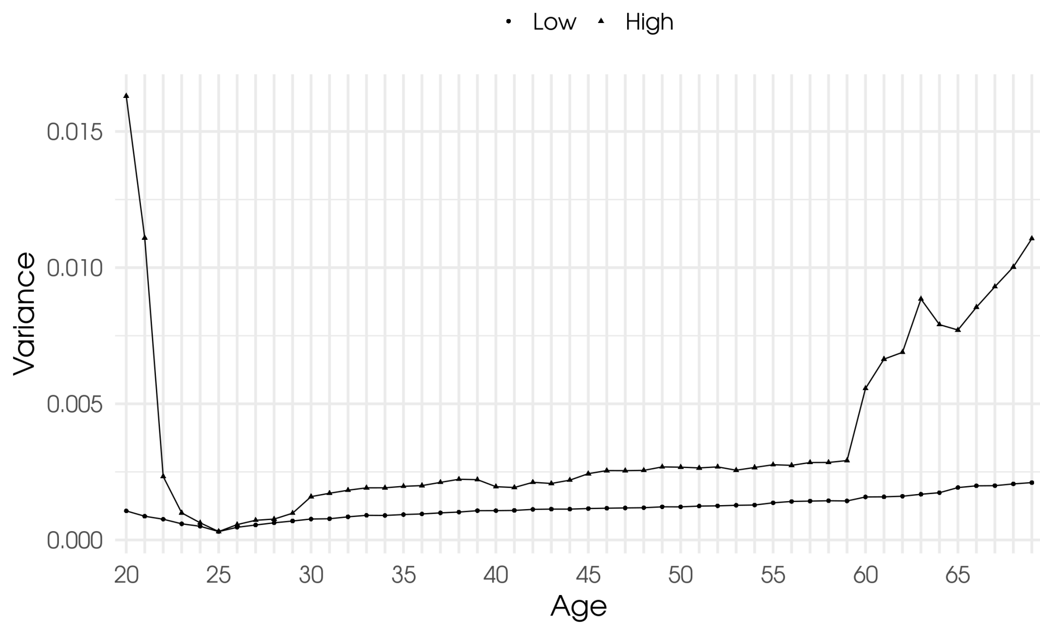
Figure 2 illustrates the variance of the fixed-effect estimation for each age by gender and education, using occupational volatility as a measure, as described by Lin and Hung (2022). Overall, the findings confirm that occupational volatility increases in later life (Figure 2 (a)). Compared to that at age 25, the volatility increases linearly until age 59. After age 60, the increase in volatility is steeper than that in the midlife period. This pattern is observed for both men and women (see Figure 2 (b)) but not across educational groups (see Figure 2 (c)). Contrary to previous studies (Neal 1999; D. Autor and Dorn 2009; Gathmann and Schönberg 2010), which have suggested the presence of career stability in the midlife period, these findings indicate a constant increase in occupational volatility for both men and women across the life course, as recently suggested by Bihagen, Shahbazian, and Kjellsson (2024). However, for different educational groups, volatility remains stable before age 59, except for those aged 20 to 22 years among those with higher education[2]. After age 60, the variance significantly increases for those with a higher level of education but not for those with a lower level of education. In summary, careers in later life are not merely a continuum of midlife careers but instead represent a distinct phase with increased occupational volatility as workers retire, change occupations, and re-enter the labor market.

[2] The high variance in the 20–22 age group is due to the absence of college graduates in this age range. Compared to age 25, the sample includes only vocational school and 2-year college graduates, resulting in higher variance.

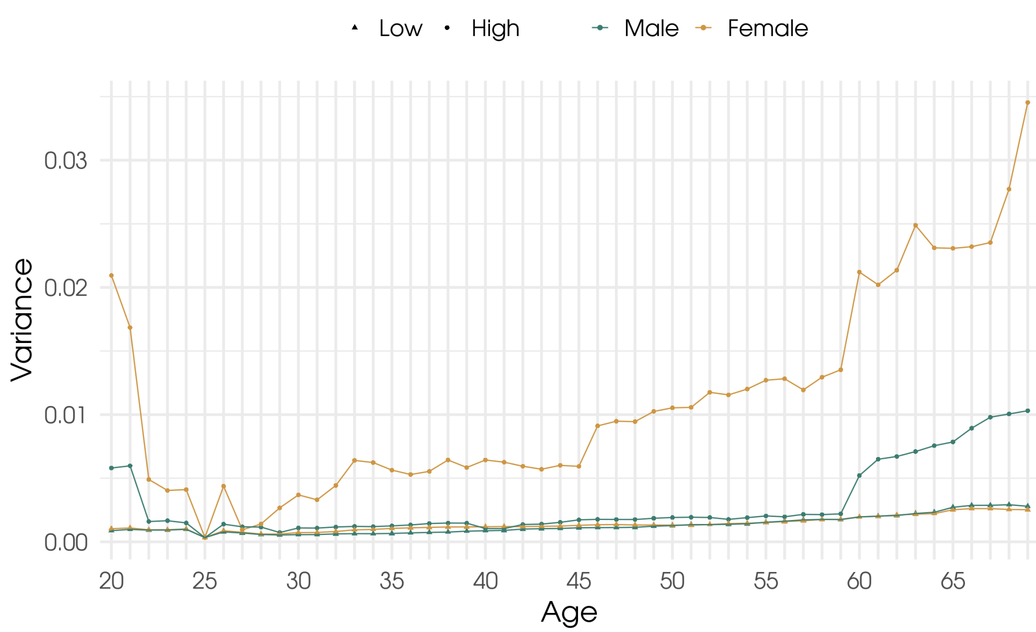
(a) Overall



(b) Gender



(c) Education



(d) Gender and Education

Figure 2: Variance in Analytical Skill Usage in Each Age by Subgroups
Note: Data are from the SSM2015 matched to data from the O-NETJ. Values are the squared standard errors calculated from the fixed-effect estimation for each age by gender and education. Number of observations = 49,804. Table S1 shows the standard errors of the fixed-effect estimation in each age.

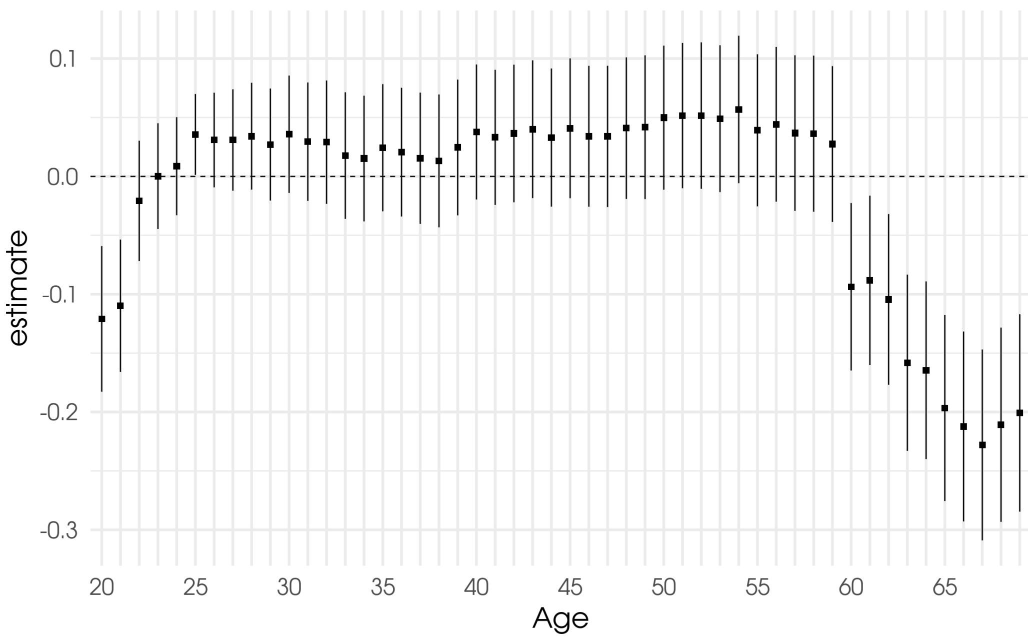
Occupational Skill Trajectory over the Life Course

To examine the occupational skill trajectory while accounting for selection and the age-period-cohort identification problem, Figure 3 presents the predictive values of analytical skill at each age by gender and education. As shown in Figure 3 (a), the skill level increases in the early 20s and stabilizes from the late 20s to the 50s. After age 60, the skill level substantially decreases.

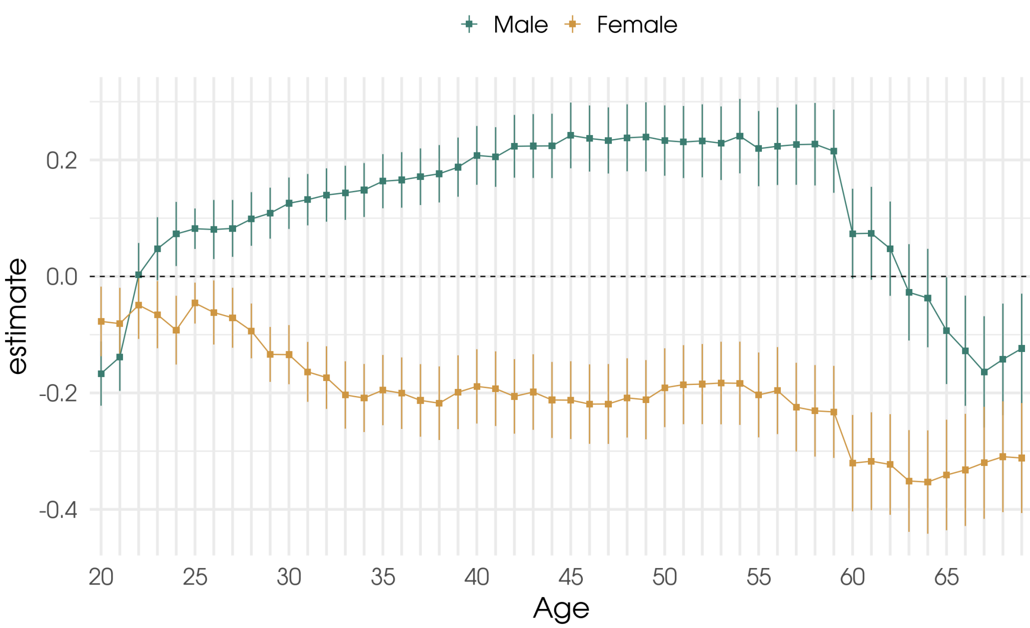
Figure 3 (b) confirms that the gendered skill trajectories observed in early- to mid-career patients do not persist into later life. Initially, there is no skill gap in the early 20s; however, a gap emerges in the late 20s, with men experiencing skill upgrading and women experiencing skill downgrading. Women's skill downgrading stops around the mid-30s, and their skill level remains stable until the mid-50s. In contrast, men's skill upgrading continues until approximately the mid-40s, and their higher skill level persists until age 60. After age 60, the skill level decreases for both men and women but do so more significantly for men. Consequently, the gender gap in analytical skill usage mostly closes after age 65, primarily due to a decline in men's skill levels.

Figure 3 (c) illustrates the analytical skill trajectory by education level. The difference between workers with a higher level of education and those with a lower level of education is evident at the entry level and persists throughout their careers. Although the skill level declines after age 60, the degree of decline is similar across educational levels, and the initial gap remains unchanged. Thus, the gap in analytical skill usage by education persists throughout the life course.

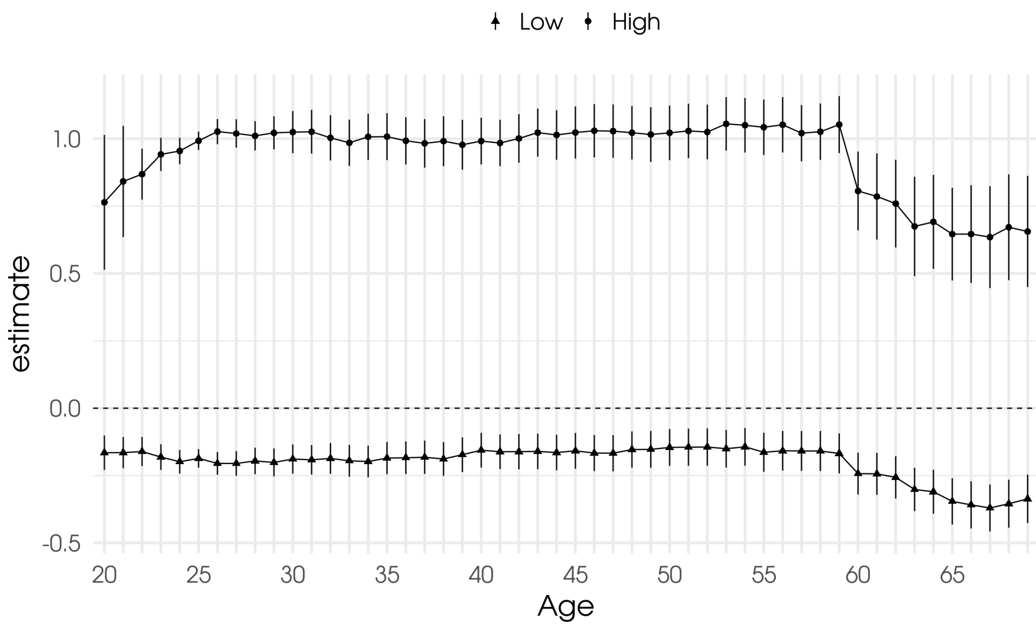
Finally, Figure 3 (d) shows the analytical skill trajectory by both gender and education. Within the same educational group, there is no observed gender gap in analytical skill usage for those with a higher level of education. However, a gender gap exists for those with a lower level of education. Men with a lower level of education exhibit greater analytical skill usage than women with a lower level of education, although their skill level is still lower than that of women with a higher level of education. This indicates that gender and education intersect to shape occupational skill trajectories.



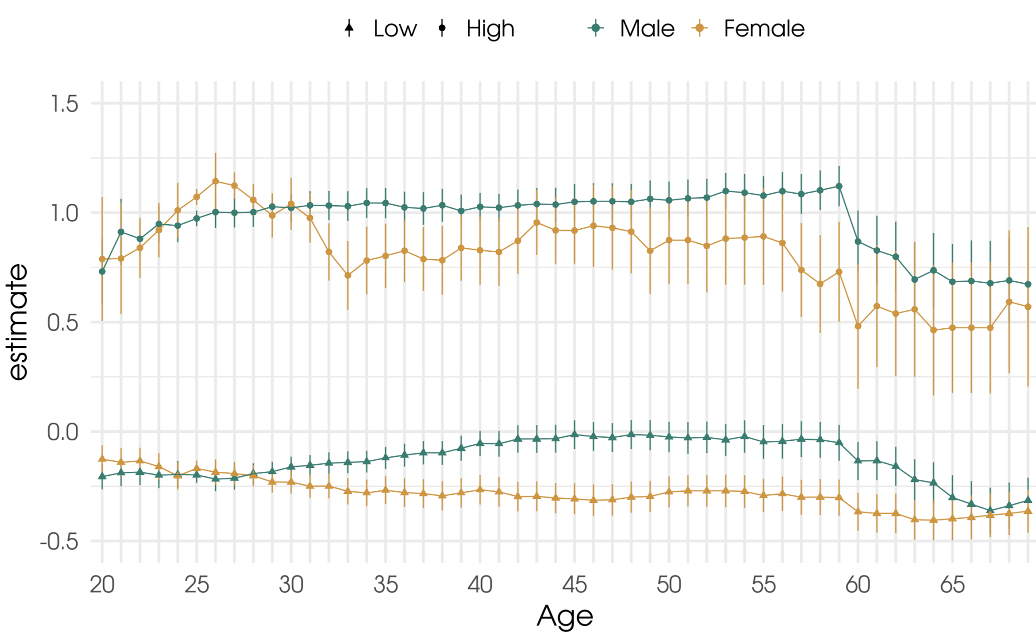
(a) Overall



(b) Gender



(c) Education



(d) Gender and Education

Figure 3: Predictive Values of Analytical Skill Usage from Fixed Effect by Subgroups
Note: Data are from the SSM2015 matched to data from the O-NETJ. Values are estimated from the fixed-effect estimation for each age by gender and education. Number of observations = 49,804. Table S1 shows the coefficient of the fixed-effect estimation in each age.

Discussion and Conclusion

In this study, I investigate the long-term analytical skill trajectory from ages 20 to 69 according to gender and education. Previous studies have assumed that workers' careers stabilize from the early life period to the midlife period and that one's later-life period is a continuum of one's midlife career. This study challenges the conventional view by showing that occupational volatility increases again later in life. Mandatory retirement, functional decline, and ageism can contribute to this increase in occupational volatility. These mechanisms likely lead to a decrease in analytical skill usage in later life, particularly affecting men and those with a higher level of education, who generally enjoy higher analytical skill usage in their early to midlife careers.

The analyses in this study confirm that occupations become more volatile later in life than in the midlife period. First, except for those with a lower level of education, the variance increases nonlinearly in later life. Although volatility increases during the early and middle life periods overall, it is even greater in the later-life period. Among the different educational groups, only those with higher education levels exhibit significant volatility in later life. This can be attributed to occupational segregation; i.e., individuals with higher levels of education can engage in a wider range of occupations (e.g., doctors and lawyers). Some people with a higher level of education are subject to mandatory retirement (e.g., in managerial occupations), while others can continue their occupations, leading to greater volatility later in life. This means that analytical skill usage varies more in later life.

Second, the volatility in analytical skill usage appears as a decrease in skill level. Workers use less analytical skill in the later-life period than they do in the midlife period. This decrease equalizes the gap in analytical skill usage by gender but not by education. The gender gap disappears after age 65, while the educational gap persists beyond the 60s. One possible explanation is that education serves as general human capital, making those with a higher level of education less susceptible to ageism from employers. Another explanation is that individuals with a higher level of education, such as lawyers and business management consultants, engage in professional occupations without mandatory retirement, making them less likely to face mandatory retirement.

The results of this study contribute to previous research by showing that divergent pathways in early careers do not necessarily continue into later life. Rather, advantages acquired in early careers can be lost later in life, as suggested by the age-as-leveler hypothesis (Corna 2013); this is particularly true for men. While it is important to investigate how labor market inequality diverges by setting up observation windows for the early career period, understanding how such inequality converges is also important. This study shows both the convergence and maintenance of analytical skill usage in later life according to gender and education.

To understand the results of this study in other countries, it is important to consider how mandatory retirement, senescence, or ageism each contribute to the trajectory in later life. For example, in countries such as the USA and the UK, where the mandatory retirement system has been largely abandoned except within some occupations, the decrease in analytical skill usage is relatively small.

This empirical analysis is not without limitations. The O-NETJ collected information about occupational skills from incumbents in 2018. Therefore, I assume that skill levels do not change throughout the examination period. In other words, this study ignores yearly within-occupational skill changes and investigates them through an arrangement at a given age. Future studies need to decompose changes in occupational skill trajectories by several structural factors (e.g., within-occupational skill changes, skill upgrading/downgrading in the labor market, and purely age-related changes). Second, retrospective survey data have limitations due to recall bias. Retrospectively collected information tends to indicate fewer transitions than actual transitions (Anna Manzoni et al. 2010). Thus, the volatility and skill decline observed herein are lower-bound estimates than those obtained using longitudinally collected data. Despite these limitations, this study detects sizable volatility and skill decline later in life, suggesting that the results are robust to recall bias.

The analyses in this study unlock further research agendas. First, other social categories, including race, ethnicity, or disability, can be explored using the same framework; for example, white non-Hispanic workers (as a prestigious group) may be allocated to occupations with lower levels of analytical skill usage later in life. Second, cohort dynamics can be examined. The cohort born in 1936–1945 experienced rapid economic growth and the expansion of the manufacturing industry, where manual skill was more rewarded than analytical skill. However, subsequent cohorts may have experienced the expansion of the service industry, where analytical skill is more rewarded.

References

Adserà, Alícia, Ana M. Ferrer, and Virginia Hernanz. 2023. "Differences in Skill Requirements Between Jobs Held by Immigrant and Native Women Across Five European Destinations." *Population Research and Policy Review* 42 (3): 38. https://doi.org/10.1007/s11113-023-09784-0.

Autor, David H, and Michael J Handel. 2013. "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages." *Journal of Labor Economics* 31 (S1): S59–96. https://doi.org/10.1086/669332.

Autor, David, and David Dorn. 2009. "This Job is 'Getting Old': Measuring Changes in Job Opportunities using Occupational Age Structure." *American Economic Review* 99 (2): 45–51. https://doi.org/10.1257/aer.99.2.45.

Bihagen, Erik, Roujman Shahbazian, and Sara Kjellsson. 2024. "Later and less? New evidence on occupational maturity for Swedish women and men." *Research in Social Stratification and Mobility*, 100884. https://doi.org/10.1016/j.rssm.2023.100884.

Cahill, Kevin E, and Joseph F Quinn. 2020. "The Importance of Gradual Retirement in America Today." *Public Policy & Aging Report* 30 (3): 107–12. https://doi.org/10.1093/ppar/praa013.

Carlsson, Magnus, and Stefan Eriksson. 2019. "Age discrimination in hiring decisions: Evidence from a field experiment in the labor market." *Labour Economics* 59: 173–83. https://doi.org/10.1016/j.labeco.2019.03.002.

Carr, Dawn C, Christina Matz, Miles G Taylor, and Ernest Gonzales. 2021. "Retirement Transitions in the United States: Patterns and Pathways From Full-Time Work." *Public Policy & Aging Report* 31 (3): 71–77. https://doi.org/10.1093/ppar/prab013.

Cheng, Siwei. 2014. "A Life Course Trajectory Framework for Understanding the Intracohort Pattern of Wage Inequality." *American Journal of Sociology* 120 (3): 633–700. https://doi.org/10.1086/679103.

Cheng, Siwei, and Barum Park. 2020. "Flows and Boundaries: A Network Approachto Studying Occupational Mobilityin the Labor Market." *American Journal of Sociology* 126 (3): 577–631.

Cheng, Siwei, and Xi Song. 2019. "Linked Lives, Linked Trajectories: Intergenerational Association of Intragenerational Income Mobility." *American Sociological Review* 84 (6): 1037–68. https://doi.org/10.1177/0003122419884497.

Corna, Laurie M. 2013. "A life course perspective on socioeconomic inequalities in health: A critical review of conceptual frameworks." *Advances in Life Course Research* 18 (2): 150–59. https://doi.org/10.1016/j.alcr.2013.01.002.

Damaske, Sarah, and Adrianne Frech. 2016. "Women's Work Pathways Across the Life Course." *Demography* 53 (2): 365–91. https://doi.org/10.1007/s13524-016-0464-z.

DiPrete, Thomas A., and Gregory M. Eirich. 2006. "Cumulative Advantage as a Mechanism for Inequality: A Review of Theoretical and Empirical Developments." *Annual Review of Sociology* 32 (1): 271–97. https://doi.org/10.1146/annurev.soc.32.061604.123127.

Doren, Catherine, and Katherine Y. Lin. 2019. "Diverging Trajectories or Parallel Pathways? An Intersectional and Life Course Approach to the Gender Earnings Gap by Race and Education." *Socius* 5: 2378023119873816. https://doi.org/10.1177/2378023119873816.

Ferraro, Kenneth F., Tetyana Pylypiv Shippee, and Markus H. Schafer. 2008. "Cumulative Inequality Theory for Research on Aging and the Life Course." In *Handbook of Theories of Aging*, edited by Merril Silverstein, Vern L. Bengtson, Norella Putney, and Daphna Gans, 2nd edition, 413–33. Springer.

Gathmann, Christina, and Uta Schönberg. 2010. "How General Is Human Capital? A Task-Based Approach." *Journal of Labor Economics* 28 (1): 1–49. https://doi.org/10.1086/649786.

Handel, Michael J. 2020. "Job Skill Requirements: Levels and Trends." *MIT Work of the Future Working Paper*.

Higo, Masa, and Thomas R. Klassen. 2015. *Retirement in Japan and South Korea : the past, the present and the future of mandatory retirement*. New York: Routledge.

Horowitz, Jonathan, and Sagi Ramaj. 2023. "Educational Expansion, Fields of Study, and the Gender Gap in Analytic Skill Usage On The Job." *Research in Social Stratification and Mobility*, 100877. https://doi.org/10.1016/j.rssm.2023.100877.

Jarvis, Benjamin F., and Xi Song. 2017. "Rising Intragenerational Occupational Mobility in the United States, 1969 to 2011." *American Sociological Review* 82 (3): 568–99. https://doi.org/10.1177/0003122417706391.

Jonsson, Jan O, David B Grusky, Matthew Di Carlo, Reinhard Pollak, and Mary C Brinton. 2009. "Microclass Mobility: Social Reproduction in Four Countries." *American Journal of Sociology* 114 (4): 977–1036. https://doi.org/10.1086/596566.

Kohler, Ulrich, Fabian Class, and Tim Sawert. 2023. "Control variable selection in applied quantitative sociology: a critical review." *European Sociological Review*. https://doi.org/10.1093/esr/jcac078.

Kondo, Ayako, and Hitoshi Shigeoka. 2017. "The Effectiveness of Demand-Side Government Intervention to Promote Elderly Employment: Evidence from Japan." *ILR Review* 70 (4): 1008–36. https://doi.org/10.1177/0019793916676490.

Korekawa, Yu. 2018. "Migration Transition in Japan and Its Mid- to Long-term Consequence: Beyond the Japanese Exceptionalism." *Migration Policy Review* 10: 13–28.

Kratz, Fabian, and Josef Brüderl. 2021. "The Age Trajectory of Happiness." https://doi.org/10.31234/osf.io/d8f2z.

Lersch, Philipp M., Wiebke Schulz, and George Leckie. 2020. "The Variability of Occupational Attainment: How Prestige Trajectories Diversified within Birth Cohorts over the Twentieth Century." *American Sociological Review* 85 (6): 1084–1116. https://doi.org/10.1177/0003122420966324.

Lin, Ken-Hou, and Koit Hung. 2022. "The Network Structure of Occupations: Fragmentation, Differentiation, and Contagion." *American Journal of Sociology* 127 (5): 1551–601. https://doi.org/10.1086/719407.

Liu, Yujia, and David B Grusky. 2013. "The Payoff to Skill in the Third Industrial Revolution." *American Journal of Sociology* 118 (5): 1330–74. https://doi.org/10.1086/669498.

Lu, Yao, Julia Shu-Huah Wang, and Wen-Jui Han. 2017. "Women's Short-Term Employment Trajectories Following Birth: Patterns, Determinants, and Variations by Race/Ethnicity and Nativity." *Demography* 54 (1): 93–118. https://doi.org/10.1007/s13524-016-0541-3.

Lundberg, Ian, Rebecca Johnson, and Brandon M. Stewart. 2021. "What Is Your Estimand? Defining the Target Quantity Connects Statistical Evidence to Theory." *American Sociological Review* 86 (3): 532–65. https://doi.org/10.1177/00031224211004187.

Manzoni, A, J Harkonen, and K U Mayer. 2014. "Moving On? A Growth-Curve Analysis of Occupational Attainment and Career Progression Patterns in West Germany." *Social Forces* 92 (4): 1285–1312. https://doi.org/10.1093/sf/sou002.

Manzoni, Anna, Jeroen K. Vermunt, Ruud Luijkx, and Ruud Muffels. 2010. "Memory Bias in Retrospectively Collected Employment Careers: A Model-based Approach to Correct for Measurement Error." *Sociological Methodology* 40 (1): 39–73. https://doi.org/10.1111/j.1467-9531.2010.01230.x.

Mouw, Ted, Arne L Kalleberg, and Michael A Schultz. 2024. "'Stepping-Stone' versus 'Dead-End' Jobs: Occupational Structure, Work Experience, and Mobility Out of Low-Wage Jobs." *American Sociological Review*. https://doi.org/10.1177/00031224241232957.

Mugiyama, Ryota, and Kota Tagami. 2024. "Matching of Japanese O-NET to SSM Occupational Classification and the Application: The Case of Wage Returns to Skills." *Sociological Theory and Methods* 39 (1).

National, Institute of Population and Social Security Research. 2023. "Population Statistics of Japan 2023."

Neal, Derek. 1999. "The Complexity of Job Mobility among Young Men." *Journal of Labor Economics* 17 (2): 237–61. https://doi.org/10.1086/209919.

OECD. 2020. "OECD Employment Outlook 2023." *OECD Employment Outlook*. https://doi.org/10.1787/19991266.

Pearl, Judea. 2009. *Causality : Models, Reasoning, and Inference*. 2nd ed. Cambridge: Cambridge University Press.

Radl, Jonas. 2013. "Labour Market Exit and Social Stratification in Western Europe: The Effects of Social Class and Gender on the Timing of Retirement." *European Sociological Review* 29 (3): 654–68. https://doi.org/10.1093/esr/jcs045.

Roscigno, Vincent J., Sherry Mong, Reginald Byron, and Griff Tester. 2007. "Age Discrimination, Social Closure and Employment." *Social Forces* 86 (1): 313–34. https://doi.org/10.1353/sof.2007.0109.

Spence, Michael. 1973. "Job Market Signaling*." *The Quarterly Journal of Economics* 87 (3): 355–74. https://doi.org/10.2307/1882010.

Struffolino, Emanuela. 2019. "Navigating the early career: The social stratification of young workers' employment trajectories in Italy." *Research in Social Stratification and Mobility* 63: 100421. https://doi.org/10.1016/j.rssm.2019.100421.

Sullivan, Paul. 2010. "Empirical evidence on occupation and industry specific human capital." *Labour Economics* 17 (3): 567–80. https://doi.org/10.1016/j.labeco.2009.11.003.

Tomaskovic-Devey, Donald, Melvin Thomas, and Kecia Johnson. 2005. "Race and the Accumulation of Human Capital across the Career: A Theoretical Model and Fixed-Effects Application." *American Journal of Sociology* 111 (1): 58–89. https://doi.org/10.1086/431779.

Villarreal, Andrés. 2019. "The U.S. Occupational Structure: A Social Network Approach." *Sociological Science* 7: 187–221.

Visser, Mark, Maurice Gesthuizen, Gerbert Kraaykamp, and Maarten H J Wolbers. 2018. "Labor Market Vulnerability of Older Workers in the Netherlands and its Impact on Downward Mobility and Reduction of Working Hours." *Work, Aging and Retirement* 4 (3): 289–99. https://doi.org/10.1093/workar/wax017.

Visser, Mark, Maurice Gesthuizen, Gerbert Kraaykamp, and Maarten H. J. Wolbers. 2016. "Inequality among Older Workers in the Netherlands: A Life Course and Social Stratification Perspective on Early Retirement." *European Sociological Review* 32 (3): 370–82. https://doi.org/10.1093/esr/jcw013.

Winkle, Zachary Van, and Anette Eva Fasang. 2020. "Parenthood Wage Gaps Across the Life Course: A Comparison by Gender and Race." *Journal of Marriage and Family* 82 (5): 1515–33. https://doi.org/10.1111/jomf.12713.

Wise, David A. 2010. "Facilitating longer working lives: International evidence on why and how." *Demography* 47 (Suppl 1): S131–49. https://doi.org/10.1353/dem.2010.0000.

Supplementary Materials

Regression Coefficients and Standard Errors from Fixed Effect Estimation of Analytical Skill Usage on Age, Gender and Education

Table S1: Fixed Effect Estimation Coefficients and Standard Errors

	Model 1	Model 2	Model 3	Model 4
GDP	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
UnempRate	-0.014	-0.015	-0.015	-0.016
	(0.011)	(0.012)	(0.011)	(0.012)
Age20	0.060*	0.000	0.061*	0.016
	(0.026)	(0.017)	(0.027)	(0.019)
Age21	0.054*	0.016	0.053*	0.031
	(0.022)	(0.019)	(0.023)	(0.021)
Age22	0.042*	0.018	0.052*	0.030
	(0.019)	(0.017)	(0.021)	(0.020)
Age23	0.019	0.001	0.025	0.008
	(0.014)	(0.016)	(0.017)	(0.020)
Age24	0.000	0.003	0.003	0.012
	(0.011)	(0.017)	(0.013)	(0.021)
Age26	-0.010	-0.009	-0.017	-0.021
	(0.010)	(0.014)	(0.012)	(0.018)
Age27	-0.010	-0.009	-0.014	-0.017
	(0.013)	(0.013)	(0.015)	(0.015)
Age28	0.001	0.006	0.000	0.002
	(0.015)	(0.011)	(0.018)	(0.012)
Age29	-0.005	0.018	-0.009	0.014
	(0.017)	(0.010)	(0.020)	(0.012)
Age30	0.011	0.034**	0.007	0.032*
	(0.019)	(0.011)	(0.022)	(0.013)
Age31	0.007	0.040**	0.004	0.042**
	(0.019)	(0.012)	(0.022)	(0.013)
Age32	0.012	0.050**	0.012	0.054**
	(0.020)	(0.013)	(0.023)	(0.015)
Age33	0.014	0.055**	0.016	0.060**

	Model 1	Model 2	Model 3	Model 4
	(0.021)	(0.014)	(0.024)	(0.016)
Age34	0.025	0.062**	0.025	0.064**
	(0.021)	(0.014)	(0.024)	(0.016)
Age35	0.039	0.080**	0.039	0.084**
	(0.022)	(0.015)	(0.025)	(0.017)
Age36	0.039	0.085**	0.041	0.094**
	(0.023)	(0.016)	(0.026)	(0.018)
Age37	0.039	0.092**	0.043	0.107**
	(0.023)	(0.017)	(0.026)	(0.019)
Age38	0.046	0.097**	0.048	0.108**
	(0.024)	(0.018)	(0.027)	(0.020)
Age39	0.058*	0.111**	0.064*	0.131**
	(0.025)	(0.020)	(0.028)	(0.022)
Age40	0.068**	0.132**	0.074**	0.153**
	(0.026)	(0.021)	(0.029)	(0.024)
Age41	0.067*	0.134**	0.073*	0.156**
	(0.026)	(0.021)	(0.029)	(0.024)
Age42	0.073**	0.156**	0.079**	0.180**
	(0.027)	(0.024)	(0.030)	(0.027)
Age43	0.078**	0.159**	0.082**	0.182**
	(0.028)	(0.025)	(0.031)	(0.028)
Age44	0.078**	0.160**	0.083**	0.184**
	(0.028)	(0.025)	(0.031)	(0.028)
Age45	0.087**	0.175**	0.090**	0.201**
	(0.028)	(0.026)	(0.031)	(0.030)
Age46	0.082**	0.173**	0.082**	0.198**
	(0.028)	(0.026)	(0.031)	(0.030)
Age47	0.081**	0.172**	0.081*	0.197**
	(0.028)	(0.026)	(0.031)	(0.030)
Age48	0.089**	0.181**	0.091**	0.207**
	(0.029)	(0.027)	(0.032)	(0.031)
Age49	0.092**	0.181**	0.093**	0.203**
	(0.029)	(0.027)	(0.032)	(0.031)

	Model 1	Model 2	Model 3	Model 4
Age50	0.093**	0.172**	0.094**	0.194**
	(0.029)	(0.028)	(0.032)	(0.032)
Age51	0.096**	0.176**	0.096**	0.196**
	(0.030)	(0.029)	(0.033)	(0.033)
Age52	0.099**	0.177**	0.099**	0.195**
	(0.030)	(0.029)	(0.033)	(0.034)
Age53	0.098**	0.175**	0.093**	0.184**
	(0.031)	(0.031)	(0.035)	(0.035)
Age54	0.103**	0.189**	0.099**	0.204**
	(0.033)	(0.032)	(0.036)	(0.036)
Age55	0.091**	0.176**	0.086*	0.188**
	(0.035)	(0.035)	(0.038)	(0.039)
Age56	0.101**	0.187**	0.096*	0.198**
	(0.037)	(0.037)	(0.040)	(0.042)
Age57	0.101*	0.195**	0.100*	0.211**
	(0.039)	(0.040)	(0.042)	(0.044)
Age58	0.115**	0.210**	0.113*	0.224**
	(0.041)	(0.042)	(0.044)	(0.046)
Age59	0.109*	0.203**	0.106*	0.215**
	(0.043)	(0.044)	(0.046)	(0.047)
Age60	0.049	0.126*	0.055	0.158**
	(0.046)	(0.048)	(0.048)	(0.051)
Age61	0.046	0.122*	0.056	0.162**
	(0.047)	(0.050)	(0.050)	(0.052)
Age62	0.038	0.112*	0.046	0.149**
	(0.047)	(0.050)	(0.049)	(0.052)
Age63	0.017	0.083	0.030	0.127*
	(0.048)	(0.051)	(0.050)	(0.053)
Age64	0.017	0.088	0.023	0.121*
	(0.048)	(0.052)	(0.051)	(0.054)
Age65	-0.015	0.012	-0.005	0.045
	(0.048)	(0.051)	(0.051)	(0.055)
Age66	-0.032	-0.013	-0.027	0.011

	Model 1	Model 2	Model 3	Model 4
	(0.049)	(0.053)	(0.052)	(0.056)
Age67	-0.044	-0.031	-0.042	-0.012
	(0.049)	(0.053)	(0.052)	(0.055)
Age68	-0.038	-0.014	-0.033	0.013
	(0.049)	(0.053)	(0.052)	(0.057)
Age69	-0.045	-0.017	-0.038	0.014
	(0.047)	(0.051)	(0.050)	(0.053)
Age20 × Female		0.081**		0.059
		(0.028)		(0.031)
Age21 × Female		0.042		0.019
		(0.030)		(0.033)
Age22 × Female		0.028		0.021
		(0.028)		(0.030)
Age23 × Female		0.027		0.023
		(0.027)		(0.031)
Age24 × Female		-0.015		-0.030
		(0.028)		(0.033)
Age26 × Female		0.000		0.010
		(0.026)		(0.029)
Age27 × Female		0.003		0.014
		(0.023)		(0.026)
Age28 × Female		-0.015		-0.005
		(0.019)		(0.021)
Age29 × Female		-0.066**		-0.060**
		(0.017)		(0.019)
Age30 × Female		-0.069**		-0.070**
		(0.020)		(0.022)
Age31 × Female		-0.100**		-0.101**
		(0.020)		(0.022)
Age32 × Female		-0.115**		-0.116**

	Model 1	Model 2	Model 3	Model 4
		(0.023)		(0.024)
Age33 × Female		-0.124**		-0.121**
		(0.025)		(0.027)
Age34 × Female		-0.117**		-0.115**
		(0.025)		(0.027)
Age35 × Female		-0.130**		-0.130**
		(0.027)		(0.029)
Age36 × Female		-0.143**		-0.150**
		(0.028)		(0.030)
Age37 × Female		-0.160**		-0.174**
		(0.028)		(0.031)
Age38 × Female		-0.154**		-0.166**
		(0.029)		(0.032)
Age39 × Female		-0.161**		-0.183**
		(0.030)		(0.033)
Age40 × Female		-0.188**		-0.206**
		(0.030)		(0.034)
Age41 × Female		-0.196**		-0.216**
		(0.031)		(0.034)
Age42 × Female		-0.230**		-0.255**
		(0.032)		(0.036)
Age43 × Female		-0.225**		-0.253**
		(0.033)		(0.037)
Age44 × Female		-0.227**		-0.255**

	Model 1	Model 2	Model 3	Model 4
		(0.033)		(0.037)
Age45 × Female		-0.243**		-0.274**
		(0.035)		(0.039)
Age46 × Female		-0.250**		-0.284**
		(0.036)		(0.039)
Age47 × Female		-0.250**		-0.286**
		(0.036)		(0.040)
Age48 × Female		-0.251**		-0.286**
		(0.036)		(0.040)
Age49 × Female		-0.246**		-0.273**
		(0.037)		(0.041)
Age50 × Female		-0.226**		-0.254**
		(0.037)		(0.041)
Age51 × Female		-0.227**		-0.253**
		(0.037)		(0.042)
Age52 × Female		-0.219**		-0.246**
		(0.038)		(0.042)
Age53 × Female		-0.218**		-0.234**
		(0.038)		(0.043)
Age54 × Female		-0.240**		-0.263**
		(0.039)		(0.044)
Age55 × Female		-0.236**		-0.259**
		(0.041)		(0.046)
Age56 × Female		-0.238**		-0.256**

	Model 1	Model 2	Model 3	Model 4
		(0.041)		(0.047)
Age57 × Female		-0.259**		-0.277**
		(0.042)		(0.047)
Age58 × Female		-0.261**		-0.277**
		(0.043)		(0.048)
Age59 × Female		-0.254**		-0.271**
		(0.043)		(0.048)
Age60 × Female		-0.212**		-0.256**
		(0.048)		(0.053)
Age61 × Female		-0.212**		-0.266**
		(0.050)		(0.053)
Age62 × Female		-0.207**		-0.260**
		(0.051)		(0.054)
Age63 × Female		-0.189**		-0.247**
		(0.052)		(0.056)
Age64 × Female		-0.201**		-0.251**
		(0.053)		(0.057)
Age65 × Female		-0.090		-0.140*
		(0.057)		(0.062)
Age66 × Female		-0.071		-0.112
		(0.059)		(0.063)
Age67 × Female		-0.057		-0.094
		(0.059)		(0.063)
Age68 × Female		-0.083		-0.129*
		(0.059)		(0.064)
Age69 × Female		-0.092		-0.143*
		(0.059)		(0.063)

	Model 1	Model 2	Model 3	Model 4
Age20 × Education			-0.007	-0.113
			(0.130)	(0.074)
Age21 × Education			0.024	-0.086
			(0.106)	(0.075)
Age22 × Education			-0.069	-0.050
			(0.049)	(0.039)
Age23 × Education			-0.042	-0.025
			(0.030)	(0.040)
Age24 × Education			-0.015	-0.038
			(0.022)	(0.039)
Age26 × Education			0.036	0.046
			(0.020)	(0.036)
Age27 × Education			0.019	0.033
			(0.025)	(0.031)
Age28 × Education			0.003	0.016
			(0.028)	(0.028)
Age29 × Education			0.024	0.016
			(0.032)	(0.022)
Age30 × Education			0.023	0.007
			(0.042)	(0.028)
Age31 × Education			0.017	-0.004
			(0.044)	(0.029)
Age32 × Education			0.002	-0.016
			(0.046)	(0.031)
Age33 × Education			-0.008	-0.020
			(0.047)	(0.032)
Age34 × Education			0.006	-0.007
			(0.048)	(0.032)
Age35 × Education			0.007	-0.012
			(0.049)	(0.034)
Age36 × Education			-0.008	-0.036
			(0.049)	(0.036)
Age37 × Education			-0.019	-0.059

	Model 1	Model 2	Model 3	Model 4
			(0.051)	(0.037)
Age38 × Education			-0.003	-0.044
			(0.052)	(0.038)
Age39 × Education			-0.026	-0.079*
			(0.052)	(0.039)
Age40 × Education			-0.029	-0.080*
			(0.050)	(0.034)
Age41 × Education			-0.031	-0.086*
			(0.050)	(0.035)
Age42 × Education			-0.028	-0.099*
			(0.052)	(0.041)
Age43 × Education			-0.013	-0.094*
			(0.052)	(0.041)
Age44 × Education			-0.016	-0.099*
			(0.053)	(0.042)
Age45 × Education			-0.011	-0.103*
			(0.056)	(0.045)
Age46 × Education			0.008	-0.099*
			(0.057)	(0.046)
Age47 × Education			0.010	-0.099*
			(0.057)	(0.047)
Age48 × Education			-0.002	-0.106*
			(0.057)	(0.047)
Age49 × Education			0.006	-0.085
			(0.058)	(0.048)
Age50 × Education			-0.001	-0.086
			(0.058)	(0.049)
Age51 × Education			0.006	-0.077
			(0.058)	(0.049)
Age52 × Education			0.013	-0.070
			(0.058)	(0.049)
Age53 × Education			0.038	-0.032
			(0.057)	(0.048)

	Model 1	Model 2	Model 3	Model 4
Age54 × Education			0.032	-0.055
			(0.058)	(0.049)
Age55 × Education			0.042	-0.046
			(0.059)	(0.051)
Age56 × Education			0.043	-0.036
			(0.059)	(0.051)
Age57 × Education			0.022	-0.057
			(0.060)	(0.052)
Age58 × Education			0.025	-0.051
			(0.061)	(0.052)
Age59 × Education			0.037	-0.042
			(0.061)	(0.052)
Age60 × Education			-0.022	-0.135
			(0.081)	(0.077)
Age61 × Education			-0.042	-0.169
			(0.087)	(0.086)
Age62 × Education			-0.035	-0.160
			(0.089)	(0.088)
Age63 × Education			-0.067	-0.191*
			(0.100)	(0.091)
Age64 × Education			-0.020	-0.144
			(0.096)	(0.094)
Age65 × Education			-0.043	-0.139
			(0.095)	(0.097)
Age66 × Education			-0.010	-0.095
			(0.100)	(0.103)
Age67 × Education			0.011	-0.071
			(0.104)	(0.107)
Age68 × Education			-0.017	-0.116
			(0.108)	(0.110)
Age69 × Education			-0.034	-0.140
			(0.113)	(0.111)

	Model 1	Model 2	Model 3	Model 4
Age20 × Female ×Education				0.183
				(0.155)
Age21 × Female ×Education				0.195
				(0.145)
Age22 × Female ×Education				-0.016
				(0.074)
Age23 × Female ×Education				-0.020
				(0.074)
Age24 × Female ×Education				0.101
				(0.076)
Age26 × Female ×Education				-0.036
				(0.077)
Age27 × Female ×Education				-0.067
				(0.037)
Age28 × Female ×Education				-0.095*
				(0.038)
Age29 × Female ×Education				-0.046
				(0.047)
Age30 × Female ×Education				0.010
				(0.061)
Age31 × Female ×Education				-0.012
				(0.062)
Age32 × Female ×Education				-0.045
				(0.070)

	Model 1	Model 2	Model 3	Model 4
Age33 × Female ×Education				-0.097
				(0.085)
Age34 × Female ×Education				-0.061
				(0.085)
Age35 × Female ×Education				-0.040
				(0.083)
Age36 × Female ×Education				-0.002
				(0.081)
Age37 × Female ×Education				0.029
				(0.083)
Age38 × Female ×Education				0.054
				(0.088)
Age39 × Female ×Education				0.102
				(0.086)
Age40 × Female ×Education				0.052
				(0.088)
Age41 × Female ×Education				0.070
				(0.088)
Age42 × Female ×Education				0.100
				(0.088)
Age43 × Female ×Education				0.152
				(0.087)
Age44 × Female ×Education				0.153
				(0.089)

	Model 1	Model 2	Model 3	Model 4
Age45 × Female ×Education				0.179
				(0.091)
Age46 × Female ×Education				0.235*
				(0.107)
Age47 × Female ×Education				0.245*
				(0.109)
Age48 × Female ×Education				0.225*
				(0.110)
Age49 × Female ×Education				0.175
				(0.114)
Age50 × Female ×Education				0.181
				(0.115)
Age51 × Female ×Education				0.171
				(0.115)
Age52 × Female ×Education				0.186
				(0.120)
Age53 × Female ×Education				0.127
				(0.119)
Age54 × Female ×Education				0.177
				(0.122)
Age55 × Female ×Education				0.188
				(0.125)
Age56 × Female ×Education				0.150
				(0.126)

	Model 1	Model 2	Model 3	Model 4
Age57 × Female ×Education				0.118
				(0.122)
Age58 × Female ×Education				0.101
				(0.127)
Age59 × Female ×Education				0.127
				(0.129)
Age60 × Female ×Education				0.366*
				(0.161)
Age61 × Female ×Education				0.437*
				(0.164)
Age62 × Female ×Education				0.448*
				(0.168)
Age63 × Female ×Education				0.476*
				(0.180)
Age64 × Female ×Education				0.443*
				(0.177)
Age65 × Female ×Education				0.423*
				(0.180)
Age66 × Female ×Education				0.386*
				(0.183)
Age67 × Female ×Education				0.366
				(0.185)
Age68 × Female ×Education				0.427*
				(0.197)

	Model 1	Model 2	Model 3	Model 4
Age69 × Female ×Education				0.505*
				(0.213)
Num.Obs.	49804	49804	49804	49804
R2	0.778	0.780	0.778	0.781
R2 Adj.	0.772	0.774	0.772	0.774
R2 Within	0.007	0.017	0.008	0.019
R2 Within Adj.	0.006	0.015	0.006	0.015
AIC	69294.1	68925.5	69372.4	69004.9
BIC	82077.1	82140.4	82587.4	83083.8
RMSE	0.47	0.47	0.47	0.47
Std. Errors	by: individual	by: individual & Age	by: individual	by: individual & Age
FE: individual	X	X	X	X

* p < 0.05, ** p < 0.01