4350 - Thesis in Finance

Is Degree Depreciation Happening?

A Lifecycle Analysis of Labor Income Process and Human Capital

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Contents

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Abstract

This paper estimates the labor income process and human capital trajectories of individuals with different educational degrees throughout the life cycle. Using the Panel Study of Income Dynamics, Social, Health and Economic Longitudinal File (PSID-SHELF, 1968-2019) of representative U.S. households, the study observes heterogeneity in labor income returns and human capital development across different education levels. The transitory and permanent labor income risks are heterogeneous and exhibit different patterns across cohorts and genders. Therefore, cohort and gender differences are demonstrated separately by studying individuals born in the first half of the twentieth century (1902-1951) and those born later (1952-1999). Empirical evidence confirms the phenomenon of degree depreciation, as reflected in compressed labor income curves and flattened human capital trajectories across generations, and shows strong evidence of improved gender equality in the labor market.

Keywords: *Household Finance; Labor Income; Human Capital; Education; Risk Decomposition; Gender Equality; Degree Depreciation; Life-cycle Earnings.*

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I. Introduction

In recent years, the global labor market has faced difficult challenges. Factors such as aging populations, persistently high inflation, stagnant unemployment rates, and geopolitical tension have collectively influenced labor markets around the world. At the same time, technological advancement and AI-automation have shifted the labor market's demand for talents, now favoring adaptability and digital literacy over traditional education degrees or qualifications. Many economies have experienced widespread layoffs, even among highly skilled and educated workers, and an increasing number of fresh graduates find it extremely difficult to figure out where their careers begin. This global phenomenon has raised debates and questions among the public about the economic value of education degrees and their role in shaping labor market outcomes.

The conventional thought held by many people assumes a positive correlation between educational attainment and a person's productivity, social status, and work skills, and therefore their potential for better placement, higher labor earnings, and higher individual wealth achievement. However, the situation in recent years has challenged this prevailing belief, leading many to question whether a phenomenon known as degree depreciation, meaning a decline in the economic value of academic degrees, has emerged as a new reality of the labor market. People are beginning to ask: is it still worth dedicating all the time and energy to pursuing a Master's degree, a PhD, an MBA, or other advanced degrees? The central question narrows down to one that is difficult to confront directly: is degree depreciation truly happening?

Therefore, this thesis is motivated by these current labor market conditions and aims to investigate the relationship between educational attainment and labor earnings, assessing whether empirical evidence suggests the presence of degree depreciation. The study aims to provide critical insights for students, educators, and other relevant stakeholders by evaluating the long-term economic payoffs of education degrees measured by labor income, and the corresponding financial resilience and wealth generation outcomes over the life cycle.

The research is made possible by the availability of the Panel Study of Income Dynamics, Social, Health, and Economic Longitudinal File (PSID-SHELF), covering 1968-2019 and based on longitudinal surveys of U.S. households. This dataset provides detailed and continuous follow-up information on individuals' education, income, and demographic characteristics, allowing for a comprehensive and up-to-date analysis. Unlike earlier studies constrained by limited time frames or small cross-sectional samples, the PSID-SHELF enables the tracking of individual labor earnings trajectories over longer periods and allows for a detailed examination of how returns to education vary across the life cycle.

The methodology is based on a well-established list of empirical and theoretical research on life-cycle models, including labor income estimation, labor income risk decomposition, and human capital valuation. The analysis adopts a calibrated life-cycle model to estimate individual labor income dynamics with birth-cohort fixed effects. The study by Cocco, Gomes, and Maenhout (2005) provides a framework for labor income process estimation and serves as a fundamental approach for modeling labor income process and human capital trajectories. Building on this, Catherine, Sodini, and Zhang (2023) extends the framework by focusing on counter-cyclical labor income risks, enabling a decomposition of income variance into persistent and transitory components by education level. Furthermore, the empirical strategy proposed by Gomes and Smirnova (2023), which uses first-difference data to capture cohort effects and gender differences, supports this thesis in developing further estimation while controlling for unobserved heterogeneity. Together, these methodological studies enable the methodological framework of this thesis and offer tested approaches for baseline regressions and the decomposition of labor income risks.

Building on the issues identified above, this thesis contributes to the literature in three main ways. First, it uses the PSID-SHELF dataset, allowing returns to specific degrees to be examined more precisely than in most existing studies. Second, it applies recent empirical techniques, including labor income variance decomposition and human capital estimation, to evaluate whether different degrees exhibit signs of depreciation in their economic value. Third, it incorporates gender and birth cohort differences to assess whether generational shifts affect the returns and risks associated with higher education. Together, these contributions offer a comprehensive perspective on how educational degrees shape labor income dynamics, income risk, and long-term wealth outcomes.

In summary, this thesis examines the increasingly debated issue of whether academic degrees are losing their economic value over time, a phenomenon referred to as degree depreciation. Against the backdrop of a challenging global labor market, the central research question investigates the extent to which higher educational attainment continues to translate into greater labor earnings and individual wealth accumulation across the life cycle. By estimating labor income dynamics across education levels, decomposing income risk, analyzing human capital development, and examining cohort and gender differences, this study provides empirical evidence on how education shapes long-term economic outcomes and assesses the relevance of degree depreciation in the contemporary labor market.

The remainder of this thesis is organized as follows. Section II reviews the existing literature on education, labor earnings, and human capital, outlining key theoretical foundations and empirical findings. Section III introduces the dataset, describes the key variables, and explains the data preprocessing procedures. Section IV presents the methodological framework, including labor income process estimation, labor income risk decomposition, human capital modeling, and cohort and gender-relevant analysis. Section V reports and discusses the empirical results and includes a section on limitations. Section VI concludes with the main findings, implications, and directions for future research.

II. Literature Review

Over the past several decades, the relationship between higher education and labor earnings outcomes has been at the center of both socioeconomic and academic debate. While traditional beliefs and social norms tend to support the idea of a positive correlation between educational attainment and individual earnings (Becker, 1964; Mincer, 1974), recent studies suggest that the actual returns to higher education are highly heterogeneous and context dependent, varying with broader economic and structural conditions (Card, 1999; Guvenen, 2009).

One of the key emerging concerns is the phenomenon of degree depreciation. The idea is that the economic value of an academic degree, measured by labor earnings capacity and wealth accumulation, diminishes over time. This phenomenon has attracted growing attention among researchers, policymakers, and educators (Altonji, Blom, & Meghir, 2012; Mulligan & Sala-i Martin, 1997), as it raises fundamental questions about the long-term economic returns to education and the sustainability of human capital investment. If proven to be true, the emergence of declining and heterogeneous returns to higher education may have a significant impact on future generations' educational choices and career planning.

This literature review outlines the key theoretical foundations, empirical findings, and methodological approaches that have shaped the current understanding of the relationship between education and labor income, with particular attention to how these perspectives provide a methodological foundation for the focus of this thesis.

II.1. Education and Labor Earnings Relationship

Much existing literature in labor economics and labor sociology has, over the past decades, consistently observed a positive relationship between educational attainment and labor market success, measured by earnings: the higher the level of educational attainment, the higher the earnings of workers (Becker, 1964; Card, 1999; de Wolff & van Slijpe, 1973; Miller, 1960).

Early empirical studies by Miller (1960) and de Wolff and van Slijpe (1973) examined the robustness of this correlation. In particular, de Wolff and van Slijpe (1973) illustrated that education level explained more variance in individual income than either intelligence or social background, emphasizing the dominant role of formal schooling in shaping labor market outcomes. Moreover, they found that the interaction between education and other social factors is highly nonlinear, indicating that education can reinforce other advantages with higher levels of attainment.

Card (1999) provided empirical reassessments of the causal relationship between education and wages. He reviewed a wide array of empirical methods, including instrumental variables and natural experiments, and concluded that traditional estimates of returns to schooling may understate the causal impact. More importantly, Card pointed out that marginal returns tend to be higher for individuals from disadvantaged backgrounds, suggesting that policies that expand educational access could yield disproportionately large economic benefits for those groups.

Guvenen (2009) added an important dimension to this literature by introducing the idea that labor income profiles are highly heterogeneous. His study emphasized that lifetime earnings variation is not determined solely by schooling level, but also by idiosyncratic income trajectories that vary across individuals, even within the same educational group, which will be discussed further in the labor income risk section. He showed that failing to account for these variations leads to upward bias in estimates of income persistence and may obscure how education affects income growth over time.

These findings collectively support that the labor earnings associated with educational attainment are not uniform across individuals or time. Both structural and cyclical features of the labor market and individual-specific factors are associated with the labor income dynamics.

II.2. Theories on Human Capital, Education, and Labor Earnings

The earliest theories on the economic value of education originated from Becker (1964) and Mincer (1974), who conceptualized education as an investment in human capital. Becker (1964) treated individuals' abilities as assets that can be developed through education, training, and experience, contributing to their productivity and labor earnings potential. Becker emphasized that higher education improves an individual's mental capacity and productivity, thereby leading to increased future income and consumption; college education in particular was a representative example of such investment that potentially led to higher future income.

Building upon Becker's human capital theory, Mincer (1974) formalized the relationship between education, experience, and earnings through what is now known as the Mincer earnings function. The model was developed based on the intuition that each additional year of schooling raises labor earnings, typically by 10-15% according to Mincer's estimates, and that increasing labor market experience further contributes to wage growth over the life cycle, though at a declining rate as age increases. Becker (1964) and Mincer (1974) both agreed that the returns to education are heterogeneous and that factors such as education quality, post-school investments including on-the-job training, and work experience can shape labor earnings trajectories in significantly different ways.

In addition, Heckman, Layne-Farrar, and Todd (1995) found that once factors such as regional variation and selection bias are controlled, evidence suggests that the direct impact of schooling on labor earnings may have been overstated. Similarly, Altonji et al. (2012) found in their recent work that not all types of education lead to the same labor market outcomes, pointing out that specific college majors and fields of study matter when it comes to future earnings. This shifts the focus from just how much education someone receives to what kind of credential they obtain, and whether that degree continues to carry value over time. These ideas connect directly to the debate around degree depreciation, where the value of a given qualification may change depending on broader labor market trends, technological changes, or cohort-specific factors. Gomes and Smirnova (2023) tackled the challenge of identifying age, cohort, and time effects by using first-difference estimations, which introduced an approach to eliminate cohort fixed effects while examining the influence of age and time within their framework.

Alternative versions of human capital theories, such as those proposed by Schultz (1961) and Nelson and Phelps (1966), emphasize individuals' capability and adaptability to change and to adapt to new technologies. Their perspectives argue that education enhances more than just productivity; it also improves a person's ability to adapt to innovation and shifting labor market demands. Meanwhile, Spence (1973) argued that an education degree primarily serves as a signal of individual ability and quality to employers, rather than acting as a direct contributing factor towards productivity. This is further supported by what is known as the sheepskin effect, where the attainment of a degree, rather than the number of years of schooling alone, is associated with a wage premium, reinforcing the notion of credential signaling (Hungerford & Solon, 1987). Some scholars have also argued that broader labor market dynamics, such as technological shifts or changes in skill demand, can alter the labor earning premiums associated with education independently of degree attainment (Mulligan & Sala-i Martin, 1997).

Despite these theoretical differences, these frameworks converge on the understanding that education, in a general sense, plays an important role in shaping wages, labor market behavior, human capital development, and long-term economic outcomes.

II.3. Labor Income Process and Life-Cycle Earnings

The labor income process involves modeling human capital and labor earnings trajectories to capture how an individual's income varies across the life cycle. A widely adopted specification to estimate the labor income process comes from Cocco et al. (2005), which involves modeling an individual's pre-retirement labor income as a combination of deterministic and stochastic components. The post-retirement income is modeled based on a replacement ratio as a constant fraction of pre-retirement labor income (Cocco et al., 2005; Gomes & Smirnova, 2023).

The structure involves one deterministic component that varies with age and individual characteristics, and two stochastic components: one named persistent (permanent) income shocks following a random walk, and the other named transitory income shocks (Cocco et al., 2005; Gomes & Smirnova, 2023). This specification is based on the work examining labor income dynamics by Carroll and Samwick (1997) and Gourinchas and Parker (2002), where they examined the random walk process of permanent shocks. Meanwhile, Hubbard, Skinner, and Zeldes (1995) provides empirical support by estimating that the first-order autoregressive process for income has a near-unit root, suggesting high persistence in income. Backed by this evidence, Cocco et al. (2005)'s approach captures the hump-shaped earnings profile observed empirically and has since served as a benchmark for subsequent labor economics and finance research.

II.4. Limitations in Existing Literature and Research Gaps

Despite the extensive body of literature exploring the education-earnings relationship, important gaps remain, particularly in how academic degrees are evaluated over the long term and across changing labor market conditions. Many existing studies rely on simplified classifications of educational attainment, such as having or not having a high school or college degree, without considering the diversity of degree types or the distinct value of specific qualifications. These broad groupings make it difficult to evaluate whether certain degrees, such as master's, law, or medical degrees, continue to deliver consistent economic returns or whether their value has diminished over time.

Moreover, while foundational models like those of Becker (1964) and Mincer (1974) provide strong support for a positive link between education and earnings, they do not fully account for the increasing heterogeneity in returns observed across fields of study, degree types, and individual earnings trajectories. More recent work has introduced life-cycle models and labor income process estimation (e.g., Cocco et al., 2005), but many of these studies use older or more limited datasets that cannot capture generational shifts or the evolving nature of the labor market due to their limited availability of longitudinal data.

Another limitation is the lack of variance decomposition by degree level, that is, how income risk (both persistent and transitory) varies depending on the type of degree held. While variance decomposition has been used in labor income modeling (Carroll & Samwick, 1997; Catherine et al., 2023), it is rarely applied in the context of educational credentials and seldom utilizes datasets extending beyond the early 2000s.

There may also be underlying structural shifts occurring. Over time, researchers have increasingly recognized the importance of cohort effects in understanding variations in labor income outcomes across generations. Studies comparing Baby Boomers, Generation X, and Millennials suggest that individuals born in different decades experience systematically different earnings trajectories even when controlling for education levels (Guvenen, Ozkan, & Song, 2014; Kahn, 2010; Lee & Solon, 2009).

III. Data

III.1. Data and Key Variables Overview

The dataset used for the thesis study is the Panel Study of Income Dynamics-Social, Health, and Economic Longitudinal File (PSID-SHELF, 1968-2019). PSID-SHELF is derived from the Panel Study of Income Dynamics (PSID) and includes 41 waves of surveys conducted in the United States. The longitudinal survey has been consistently carried out since 1968, and every individual who has consistently participated in the PSID is included in the PSID-SHELF. Of particular importance to this thesis topic, the dataset provides a set of harmonized measures on social characteristics such as demographics, family type, education, race, ethnicity, as well as economic characteristics ranging from individual earnings, family income, to occupations and wealth (Daumler, Friedman, & Pfeffer, 2025).

One particular key variable that has made the detailed empirical analysis possible is EDUDEGREE. Before 1984, PSID only contained a simple classification for education level based on a high school diploma or a college degree. Earlier work, such as that by Cocco et al. (2005), relied on a simpler classification based on whether individuals had no high school diploma, a high school diploma, or a college degree because this was the only classification they could find in early datasets. Since 1984, the PSID has introduced a specific question identifying the highest degree completed by each participant, and in PSID-SHELF the results are harmonized and stored in EDUDEGREE. The EDUDEGREE variable reflects educational qualifications obtained within the U.S. degree system and is considered representative due to the nationally representative sampling design of the PSID and its consistent tracking of individuals and families across multiple generations.

The EDUDEGREE variable categorizes educational attainment into six groups: “Associate’s” (AA), “Bachelor’s” (BS, BA), “Master’s” (MA, MS, MBA), “Doctoral” (PhD), “Law” (LLB, JD), and “Medical” (MD, DDS, DVM, DO), allowing for further investigation of the education-earnings relationship. By filtering the results of another education-status variable, EDULEVEL, it is possible to identify those below or without an associate degree, which can be incorporated into the EDUDEGREE classification under the group label "Others". Therefore, a total of seven different education degrees have been identified.

Another key variable is individual labor income. A total labor income variable at the individual level is available in the PSID for the years 1968-1993. According to the 1970 code book, it is:

"the sum of the actual amounts of the labor portion of farm income and business income, bonuses, overtime, commissions, professional practice, labor part of income from roomers and boarders, or business income." (Panel Study of Income Dynamics, 1970)

Beginning in 1994, PSID redefined the labor income variable composition to improve the accuracy and consistency of the income measurement (Daumler et al., 2025). According to Fullerton and Rao (2019), the updated definition of labor income includes wages and salaries, bonuses, overtime pay, tips, commissions, professional practice or trade income, market gardening, miscellaneous job income, and extra job income, while excluding farm income (Panel Study of Income Dynamics, 1994). It is important to note that farm income and the labor portion of business income are not included in the total labor income variable since 1994, but are stored separately (Fullerton & Rao, 2019). As a result, the labor income variable in PSID-SHELF includes the individual's total labor income based on the updated definition, plus the labor portion of business income while excluding farm income, allowing for a more accurate estimation of labor earnings when analyzing data from 1994 onwards (Daumler et al., 2025).

Furthermore, in PSID-SHELF, there are two labor income variables. One is obtained from the approach in the previous paragraph, which is reported in nominal terms. The other, which is used for this thesis, is constructed as total reported labor income in real U.S. dollars, adjusted to 2022 values. This updated measure includes business income but excludes farm income, allowing for a more accurate estimation of labor earnings when analyzing data from 1994 onward. To enable longitudinal analysis, the PSID-SHELF dataset adjusts all income variables to real U.S. dollars using the Personal Consumption Expenditures Price Index (PCEPI), standardizing them to a common base year 2022, and stores individual labor income in the variable EARNINDR (Daumler et al., 2025). This adjustment allows researchers to analyze income trends and make real-value comparisons over time without the confounding effects of inflation.

III.2. Data Pre-Processing and Considerations

To preprocess and obtain the master panel dataset, the PSID-SHELF dataset is first filtered by retaining observations from 1985 onward and dropping individuals who did not respond to the degree-related questions. This step is taken because the key variable EDUDEGREE was introduced in the PSID starting from 1985. Then, the EDUDEGREE variable is re-labeled by adding a value level zero to identify degree attainments below or without an Associate's degree. The label values and corresponding text tags after pre-processing are: 0 "Below or without Associate's" (also referred to as "Others" in later analysis), 1 "Associate's degree (AA)", 2 "Bachelor's degree (BA, BS)", 3 "Master's degree (MA, MS, MBA)", 4 "Doctoral degree (PhD)", 5 "Law degree (LLB, JD)", and 6 "Medical degree (MD, DDS, DVM, DO)". See Table A5 for detailed degree definitions.

Second, only those observations whose aggregate labor earnings variable EARNINDR (real value adjusted to 2022 USD) is greater than zero are kept. Employment status across working age is also considered, where only individuals with a valid working status throughout their working-age years are considered, and those observations with temporary lay-off or unemployment records are dropped. This restriction is necessary because the survey has been conducted biannually since the late 1990s, during which any extended periods of unemployment between waves could distort the accuracy of labor income process estimation. As a result, this step ensures consistent income flows and non-zero log earnings over the life cycle.

Third, a birth-cohort variable is generated based on the year of birth variable BIRTHYEAR, by grouping individuals into five-year intervals. In total, there are twenty cohorts, with label values ranging from 1 to 20, corresponding to birth years from 1902 to 1999. This step facilitates the extension of current literature by enabling the investigation of cohort effects and the examination of differences across cohorts.

III.3. Data Quality and Structure

After data pre-processing, the master panel dataset has a sufficiently large sample size for regression analysis and is balanced across years, as illustrated in the distribution table below.

Table I: Distribution of Educational Degree Attainment in the PSID-SHELF Sample

Year	**Others**	**Associate**	**Bachelor**	**Master**	**Doctoral**	**Law**	**Medical**	**Total**
1994	37	446	1,341	353	47	50	35	2,309
1995	35	468	1,348	358	45	51	34	2,339
1996	35	481	1,396	350	44	47	35	2,388
1997	29	375	1,192	279	35	40	33	1,983
1999	28	423	1,284	303	38	43	36	2,151
2001	34	466	1,406	305	39	47	47	2,345
2003	34	511	1,536	343	40	49	48	2,560
2005	40	534	1,650	366	41	44	47	2,722
2007	46	572	1,761	350	43	46	51	2,869
2009	60	815	1,773	690	92	54	123	3,607
2011	101	804	1,826	681	79	53	63	3,730
2013	100	837	1,851	733	76	64	56	3,717
2015	92	840	1,911	744	67	58	46	3,658
2017	103	861	1,961	799	70	55	37	3,886
2019	94	883	2,053	808	65	54	41	3,998
Total	**919**	**9,310**	**24,360**	**7,466**	**829**	**762**	**677**	**44,323**

Table I shows that the sample size increases over time, with Bachelor's and Master's degree holders making up the largest groups, while Doctoral, Law, and Medical degrees remain relatively small across all survey years. For most degree categories and years, the number of observations is at or above 30, with only a few falling slightly below this threshold, which remains sufficient for regression analysis.

IV. Methodology

The methodology is developed based on the work of Cocco et al. (2005) and Gomes and Smirnova (2023). This section discusses the theoretical framework, hypotheses, model specifications, and estimation strategies for the labor income process, labor income risk decomposition, human capital, and cohort effects.

IV.1. Labor Income Process and Replacement Ratio

In labor income estimation, Y_{it} represents the aggregate income of individual i at time t. Z_{it} is a vector that includes time-varying individual characteristics such as household size, marital status, and gender. The cohort fixed effect $c_{k(i)}$ accounts for relevant characteristics of birth cohorts, grouped in five-year intervals. The term v_{it} denotes the persistent component of the labor income process, which is modeled as a random walk consisting systematic income shocks and permanent idiosyncratic income shocks, whereas ϵ_{it} captures the transitory component of labor income, representing transitory idiosyncratic income shocks assumed to be independently and identically distributed (i.i.d.) (Cocco et al., 2005; Gomes & Smirnova, 2023).

Baseline Labor Income Process with Birth-Cohort Fixed Effects:

$$\log Y_{it} = \mu_{it} + v_{it} + \epsilon_{it} \tag{1}$$

$$\log Y_{it} = [\beta_0 + f(t, Z_{it})] + c_{k(i)} + v_{it} + \epsilon_{it} \tag{2}$$

$$\log Y_{it} = \left[\beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Age}_{it}^2 + \beta_3 \text{Age}_{it}^3 + \sum_j \beta_j Z_{it}\right] + c_{k(i)} + v_{it} + \epsilon_{it} \tag{3}$$

The post-retirement labor income is assumed to be fixed and is estimated by a deterministic function of the labor income in the last year of working life, where the deterministic ratio is called the replacement ratio λ. Following Catherine et al. (2023), the retirement income component is measured as the average income for retired 65-year-olds, and the pre-retirement labor income component is the average income for non-retired 64-year-olds, calculated separately by education group. Post-retirement income is modeled as a constant proportion λ of the last working year's labor income.

The labor income process estimation follows the assumption in Cocco et al. (2005) and Gomes and Smirnova (2023) that each individual's life cycle is divided into two periods: working life ($t \leq T$) and post-retirement life ($T < t \leq A$), where $T = 65$ (i.e. the general U.S. retirement age set by states and the pension system) and $A = 100$ (i.e. the maximum lifespan).

Replacement Ratio:

$$\lambda = \frac{\text{Retirement Income}}{\text{Pre-Retirement Labor Income}} \tag{4}$$

It is assumed that before retirement, individuals' labor income is driven by a set of individual characteristics and follows a standard permanent–transitory decomposition, and that after retirement, they receive the fixed retirement income defined above for the remaining years of their lives (Cocco et al., 2005). Therefore, the expected labor income can be computed in the following steps.

Labor Income Process - Full Life-Cycle Estimation:

$$\log Y_{it} = \begin{cases} \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Age}_{it}^2 + \beta_3 \text{Age}_{it}^3 + \sum_j \beta_j Z_{it} + c_{k(i)} + v_{it} + \epsilon_{it}, & t \leq T \\ \log(\lambda \cdot Y_{iT}), & T < t \leq A \end{cases} \tag{5}$$

$$\Rightarrow \quad \log \hat{Y}_{it} = \begin{cases} \hat{\beta}_0 + \hat{\beta}_1 \text{Age}_{it} + \hat{\beta}_2 \text{Age}_{it}^2 + \hat{\beta}_3 \text{Age}_{it}^3 + \sum_j \hat{\beta}_j Z_{it}, & t \leq T \\ \log \lambda + \log \hat{Y}_{iT}, & T < t \leq A \end{cases} \tag{6}$$

$$\Rightarrow \quad E[Y_{it}] = \begin{cases} e^{\hat{\beta}_0 + \hat{\beta}_1 \text{Age}_{it} + \hat{\beta}_2 \text{Age}_{it}^2 + \hat{\beta}_3 \text{Age}_{it}^3 + \sum_j \hat{\beta}_j Z_{it}}, & t \leq T \\ \lambda \cdot e^{\log \hat{Y}_{iT}}, & T < t \leq A \end{cases} \tag{7}$$

IV.2. Human Capital

Human capital is calculated as the present value of an individual's expected lifetime income. The formula is based on the assumption that, once individuals enter the workforce, they do not temporarily or permanently drop out of employment. The discount rate r is set at 3%, as used in Cocco et al. (2005) and Gomes and Smirnova (2023). This rate reflects a conventional long-term real interest rate used in life-cycle and household finance models, ensuring consistency with the existing literature when valuing future income streams. $E[Y_t]$ is the expected income at time t, obtained from equation (7). Life expectancy A, retirement age T, and replacement ratios λ are the same estimates defined in Section IV.1.

Human Capital:

$$\text{Human Capital Estimation} = \sum_{t=Age}^{T} \frac{E[Y_t]}{(1+r)^{t-Age}} + \sum_{t=T+1}^{A} \frac{\lambda \cdot E[Y_T]}{(1+r)^{t-Age}} \tag{8}$$

IV.3. Labor Income Risk Decomposition

Labor income risks are reflected in the error structure of labor income process estimation (2005). As assumed in this thesis, it follows a standard permanent–transitory decomposition suggested by Carroll and Samwick (1997).

Labor Income Risk Decomposition:

Step 1: From equation (1), we can obtain the residuals $log\hat{Y}^*_{it+d}$ from labor income process estimation, which are the error terms that capture v_{it}, the persistent income risks, and ϵ_{it} captures the transitory idiosyncratic income risk. The total labor income risk is denoted as η_{it}.

$$\log \hat{Y}^*_{it+d} = \log Y_{it} - [\hat{\beta}_0 + f(t, \hat{Z}_{it})] = v_{it} + \epsilon_{it} \tag{9}$$

$$\text{where } \eta_{it} = v_{it} + \epsilon_{it}$$

Step 2: Compute the first difference for the error terms, where the error structure for each year follows the standard permanent-transitory pattern, which derives the first difference of the error term as a summation of the persistent component across time:

$$\Delta\text{Error} = r_{id} \approx \log \hat{Y}^*_{it+d} - \log \hat{Y}^*_{it} = (v_{it+d} - v_{it}) + (\epsilon_{it+d} - \epsilon_{it}) \tag{10}$$

$$\text{given} \quad v_{it} = v_{i,t-1} + u_{it}, \text{ we have } (v_{it+d} - v_{it}) = \sum_{j=1}^{d} u_{it+j}$$

$$\Rightarrow \quad r_{id} \approx \sum_{j=1}^{d} u_{it+j} + (\epsilon_{it+d} - \epsilon_{it}) \tag{11}$$

Step 3: Perform simple OLS estimation to obtain the variance components. Given the dataset, I select the most recent consecutive years from 1997-2019 where the PSID-SHELF is biennial. The simple OLS should produce two coefficients: the coefficient on the time-difference index d identifies the variance of the persistent component; the constant term (divided by two) reflects the variance of the transitory component:

$$\text{Var}(r_{id}) = d \cdot \sigma_u^2 + 2\sigma_\epsilon^2 \quad \Rightarrow \quad \text{Var}(\hat{r}_{id}) = d \cdot \hat{\sigma}_u^2 + 2\hat{\sigma}_\epsilon^2 \tag{12}$$

$$\text{where } d \in \{0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20\}$$

$$\text{b.c. Year} \in \{1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017\}$$

IV.4. Cohort and Gender Differences

The master panel dataset contains a total of 20 birth cohorts, covering individuals born between 1902 and 1999. Instead of analyzing each cohort separately, which would result in very limited sample sizes for the earliest cohorts, the focus is on the broader patterns to ensure sufficient observations within each subset. Individuals born between 1902 and 1951 are grouped into the "early cohort," also referred to in later analysis as early-borns, while those born between 1952 and 1999 form the "late cohort," also referred to as later-borns. The same methodology from Sections IV.1 to IV.3 is applied to each subset separately.

For individuals in the early cohort, an additional pre-processing step was required because EDUDEGREE is only available from 1984 onward. Many early-born individuals appear in PSID waves prior to 1984, so their education information had to be reconstructed. To do this, the first step is to filter EDUDEGREE values in the master dataset and to keep those cleanly recorded and non-missing. Then, using unique individual identifiers, each individual is matched backward through earlier PSID waves and merged their pre-1984 records. This reconstruction relies on the standard assumption in longitudinal education research that individuals do not change their highest degree after entering the labor market. This allows degree information observed after 1984 to be consistently assigned to earlier years.

To construct full life-cycle income profiles for early-born individuals, the extended cohort-analysis dataset incorporates labor income records from years prior to 1994. While the main master panel uses the post-1994 labor income definition for consistency, the extended dataset uses specifically for cohort analysis includes earlier labor income measures in order to preserve long-run earnings trajectories. This ensures that both early-borns and later-borns have complete and comparable age-income profiles.

Table II: Educational Attainment Distribution by Cohort and Gender

Cohort & Gender	Others	Associate	Bachelor	Master	Doctoral	Law	Medical	Total
1902–1951 Male	125	2,587	9,955	4,342	927	842	454	19,232
1902–1951 Female	218	1,767	5,159	2,636	285	50	27	10,142
1952–1999 Male	327	4,847	14,093	3,020	347	471	457	23,562
1952–1999 Female	644	6,367	14,206	4,601	313	373	278	26,782
Total	**1,314**	**15,568**	**43,413**	**14,599**	**1,872**	**1,736**	**1,216**	**79,718**

Table III: Educational Attainment Distribution Across Birth Cohorts

Cohort	Others	Associate	Bachelor	Master	Doctoral	Law	Medical	Total
			Early Cohort	**1902-1951**				
1902–1906	0	0	0	0	0	21	0	21
1907–1911	0	0	72	44	0	0	0	116
1912–1916	0	19	70	23	0	0	0	112
1917–1921	2	21	218	31	57	0	23	352
1922–1926	0	70	616	211	39	71	2	1,009
1927–1931	27	219	1,094	517	80	110	10	2,057
1932–1936	21	245	1,161	618	62	31	64	2,202
1937–1941	57	586	1,521	1,022	146	74	71	3,477
1942–1946	63	843	3,500	1,649	416	282	94	6,847
1947–1951	173	2,351	6,862	2,863	412	303	217	13,181
			Later Cohort	**1952-1999**				
1952–1956	203	2,733	6,471	2,377	201	283	212	12,480
1957–1961	172	2,358	5,786	1,271	78	191	190	10,046
1962–1966	117	1,528	3,910	678	121	82	133	6,569
1967–1971	136	1,014	3,011	723	46	95	63	5,088
1972–1976	94	1,204	2,654	832	92	68	38	4,982
1977–1981	121	1,150	2,770	931	64	73	43	5,152
1982–1986	84	725	2,159	549	44	36	46	3,643
1987–1991	44	382	1,253	226	12	15	9	1,941
1992–1996	0	112	282	34	2	1	1	432
1997–1999	0	8	3	0	0	0	0	11
Total	**1,314**	**15,568**	**43,413**	**14,599**	**1,872**	**1,736**	**1,216**	**79,718**

The mapped dataset is used exclusively for the cohort and gender analysis, which aims to identify broad correlations and systematic patterns rather than establish causal relationships across the four cross-classified groups: early-born males, early-born females, later-born males, and later-born females.

V. Empirical Analysis

V.1. Labor Income Process and Replacement Ratio

This subsection presents the estimated labor income profiles across educational degree categories estimated using the complete panel dataset. Labor income process is estimated from equation (7), where the expected income at each age is generated from the coefficients obtained in the baseline regression specified in equation (3). As shown, the labor income trajectories exhibit the standard concave, hump-shaped pattern before retirement. At the retirement point, income drops sharply in proportion to the replacement ratio associated with each education group, remaining flat thereafter based on the assumption of a fixed post-retirement income stream.

Figure I: Labor Income Process by Education Degrees

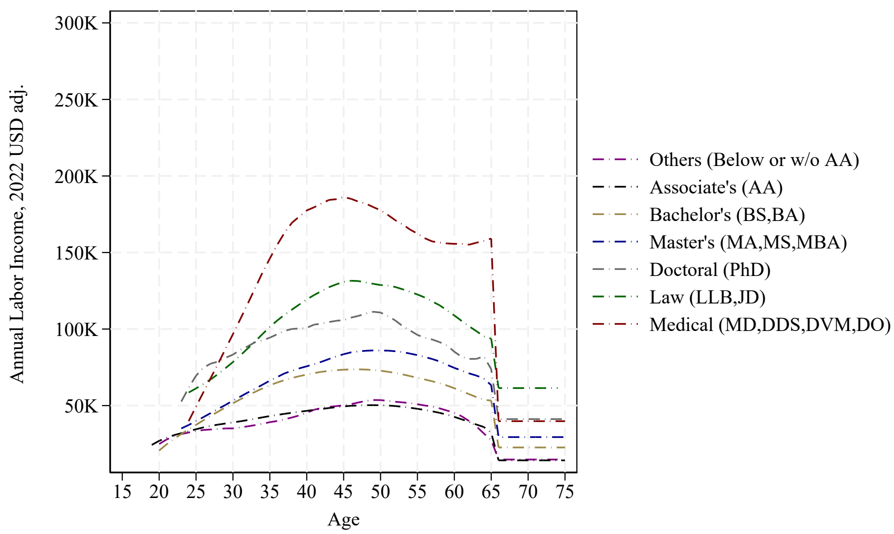


Figure I illustrates the differences in the labor income profiles across educational degrees. The first pattern observed is the timing of labor market entry. Individuals with lower educational attainment, especially Others, Associate's and Bachelor's degrees, tend to start working earlier, typically around age 20, with an initial annual income below \$25K. In contrast, individuals pursuing advanced degrees, particularly Doctoral and Law degrees, enter the labor market 3-5 years later, beginning their careers with substantially higher earnings, often above \$50K. This timing difference is consistent with the additional years required to complete higher degrees, which delays the corresponding full-time labor market participation.

The second pattern lies in the achievable labor income peak. The pre-retirement income hierarchy follows a clear order:

$$\text{Medical} > \text{Law} > \text{Doctoral} > \text{Master} > \text{Bachelor} > \text{Others} \approx \text{Associate}.$$

This supports the conventional view that higher educational attainment is associated with higher peak earnings. Associate's degree holders do not appear to gain a meaningful earnings advantage over Others. Their income trajectories remain similarly flat with a peak around $50K.

Another comparison can be made between Bachelor's and Master's trajectories. Their income profiles are nearly identical early in the life cycle, with divergence appearing only after about age 35, when Master's degree holders begin to earn more. Differences in the slope and speed of income growth are also visible. Medical degree holders exhibit the steepest development of labor income, overtaking all other groups by age 30 and reaching a peak of around $180K in their 40s.

Post-retirement patterns, however, deviate from the pre-retirement hierarchy. The post-retirement income ranking follows:

$$\text{Law} > \text{Doctoral} > \text{Medical} > \text{Master} > \text{Bachelor} > \text{Others} \approx \text{Associate}.$$

Despite enjoying the highest peak earnings during their working years, medical degree holders experience one of the sharpest income drops at retirement, falling to levels comparable to those of Doctoral degree holders. Meanwhile, Law degree holders maintain the highest post-retirement income around $60K, exceeding all other groups. No other group retains an annual labor income of more than $50K after retirement.

Overall, educational degrees differ not only in starting income and peak income levels, but also in the timing of labor market entry, the steepness of income growth, and the stability of income approaching and following retirement.

Table IV: Replacement Ratios (λ) by Education Attainment

Degrees	**Pre-retirement Component ($)**	**Retirement Component ($)**	**Replacement Ratio (λ)**
Others	29,022	14,879	0.513
Associate	49,700	26,750	0.538
Bachelor	86,031	50,146	0.583
Master	79,429	48,029	0.605
Doctoral	145,160	65,757	0.453
Law	149,403	97,995	0.656
Medical	195,374	47,618	0.244

Following the discussion above, the post-retirement income pattern can be explained through the combined effect of pre-retirement income levels and heterogeneous replacement ratios (λ) across education levels. Table IV shows that Medical degree holders, despite earning the highest pre-retirement component of approximately $195K, have the lowest replacement ratio at just 0.244. This means that upon retirement, they experience the sharpest proportional decline in income, falling to an average of about $47K. This sharp decline may reflect the occupation-specific nature of medical careers: high earnings during working years often rely on intensive, specialized labor that does not translate proportionally into pension benefits or post-retirement work opportunities.

Meanwhile, Law degree holders not only earn the second-highest pre-retirement component around $149K, but also maintain the highest replacement ratio at 0.656, and an average retirement level of nearly $98K. Their high replacement ratio makes their post-retirement financial transition extremely smoother compared to other groups. This pattern suggests that legal professionals may have comparatively strong access to retirement plans and pensions, and perhaps more opportunities for flexible consulting or part-time work after retirement. Those factors tend to help them sustain labor income levels well beyond their full-time careers.

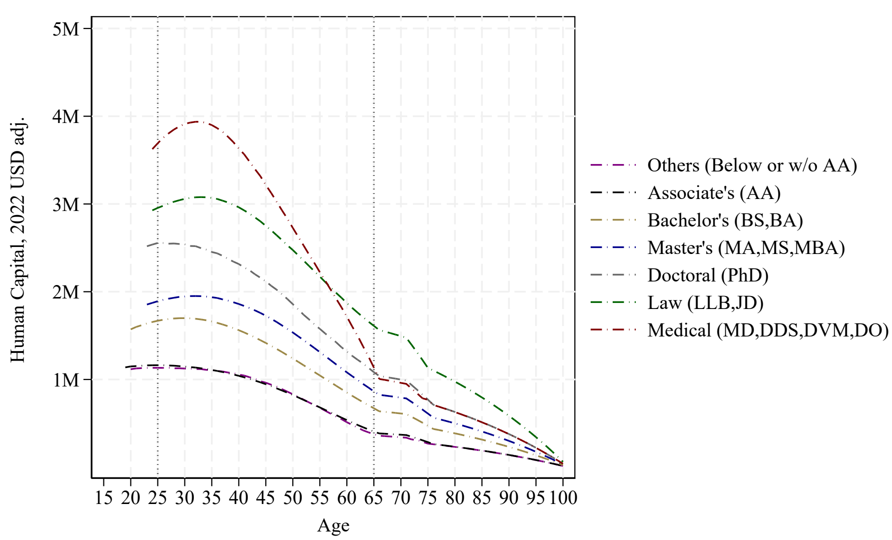
Doctoral degree holders provide another interesting case. Despite earning the third-highest before retirement is at around $145K, they have the second-lowest replacement ratio (0.453). Their post-retirement component falls to roughly $66K. This suggests a potential disconnect between the high training cost of Doctoral education and the financial protection offered during retirement.

By comparison, Associate's and Bachelor's degree holders, although earning substantially less during their working lives, exhibit moderate replacement ratios (0.538 and 0.583, respectively), leading to smoother income transitions after retirement. Individuals without a degree or below the Associate level have a slightly lower replacement ratio (0.513), but because their earnings are already low, the absolute decline in income is relatively small. This implies that while their income may be modest, the post-retirement adjustment is less severe in relative and absolute terms compared to more highly educated groups.

V.2. Human Capital

Figure II illustrates the human capital (i.e., individual wealth accumulation) over the life cycle for individuals with different educational degrees, calculated as the present value of their expected lifetime income following the equation (12). Consistent with the expectation, the overall shape of the human capital curve mirrors that of the labor income process, starting at relatively high levels during early working years, rising to a peak, and gradually declining as individuals approach and pass the retirement age. The decline post-retirement is influenced by the replacement ratios applied to income expectations after age 65.

Figure II: Human Capital by Education Degrees



In terms of absolute levels, individuals with Medical degrees exhibit the highest human capital across the first half of the life cycle, reaching a peak of approximately \$4 million in their early 30s, while the very low replacement ratio generates a steep post-retirement drop. Law degree holders also display high human capital values, peaking slightly above \$3 million and remaining the highest level when approaching retirement. Their human capital levels are consistent with both high mid-career earnings and the most favorable replacement ratio among all degree groups. Doctoral degree holders follow closely, with a slightly lower peak and a moderate decline into retirement.

At the lower end of the distribution, individuals classified as Others or Associates begin life-cycle trajectories with human capital around \$1.1 million and exhibit relatively flat profiles over time. These patterns are a direct consequence of their lower expected earnings and modest replacement ratios. Master's degree holders maintain higher human capital than Bachelor's degree holders over the entire life cycle. Master's peaks at around \$2 million, and Bachelor's peaks around \$1.6 million, which aligns with their labor income trajectories and post-retirement income replacement patterns.

Overall, Figure II mirrors the patterns observed in Figure I and Table IV. The pre-retirement human capital ranking follows:

$$\text{Medical} > \text{Law} > \text{Doctoral} > \text{Master} > \text{Bachelor} > \text{Others} \approx \text{Associate}.$$

The post-retirement human capital ranking follows:

$$\text{Law} > \text{Doctoral} \approx \text{Medical} > \text{Master} > \text{Bachelor} > \text{Others} \approx \text{Associate}.$$

Individuals with shorter educational paths tend to enter the workforce earlier and accumulate lower human capital but experience a milder decline as they approach retirement. In contrast, Medical and Law degree holders start with substantially higher human capital, yet only Law degree holders retain the highest level after retirement.

V.3. Labor Income Risk Decomposition

This section analyzes the decomposition of labor income risk across different education groups, following the permanent–transitory framework introduced in Section IV.2. Based on the residual structure of the estimated labor income process, labor income risk can be captured by two components: a permanent component σ_u^2, (i.e., persistent income shocks that affect the long-term labor income trajectory), and a transitory component σ_ε^2, (i.e., short-term income fluctuations that do not persist over time).

Table V: Labor Income Process - Birth Cohort Fixed Effects

Variable	**Others**	**Associate**	**Bachelor**	**Master**	**PhD**	**Law**	**Medical**
Dependent variable: $\log(Y_{it})$							
Age	-0.011	0.098***	0.318***	0.142***	0.115	0.449**	1.025***
	(-0.09)	(2.96)	(13.32)	(2.67)	(0.58)	(2.27)	(4.33)
Age^2	0.00148	-0.00141*	-0.00615***	-0.00186	-0.00242	-0.00936**	-0.02194***
	(0.52)	(-1.75)	(-10.65)	(-1.53)	(-0.54)	(-2.09)	(-4.17)
Age^3	-0.00002	0.00001	0.00004***	0.00001	0.00002	0.00006*	0.00015***
	(-0.84)	(0.81)	(8.47)	(0.62)	(0.50)	(1.95)	(4.03)
Family Size	-0.077***	-0.034***	-0.038***	-0.026***	0.082**	0.051	0.016
	(-2.996)	(-4.932)	(-7.281)	(-2.914)	(2.476)	(1.485)	(0.450)
Marital	0.297***	0.103***	0.140***	0.074***	-0.046	0.014	0.073
	(4.269)	(5.010)	(8.951)	(2.694)	(-0.429)	(0.124)	(0.572)
Gender	-0.555***	-0.417***	-0.487***	-0.444***	-0.597***	-0.023	-0.344***
	(-8.80)	(-25.32)	(-44.40)	(-23.05)	(-8.41)	(-0.29)	(-4.03)
Constant	10.921***	9.440***	6.542***	8.876***	10.349***	4.441	-3.237
	(7.04)	(21.56)	(20.66)	(11.82)	(3.63)	(1.60)	(-0.94)
n	919	9,309	24,360	7,466	829	762	677
T-bar	4.348	4.945	5.764	5.172	4.836	6.441	6.081
Adjusted R^2	0.1386	0.1021	0.1292	0.0980	0.1522	0.0894	0.1248
F-statistic	20.415***	143.466***	508.484***	115.805***	16.102***	4.087***	8.776***

Significance: $p < 0.10$ (*) , $p < 0.05$ (**) , $p < 0.01$ (***)

Table V presents the regression results for the labor income process estimated separately for each education group, controlling for birth-cohort effects.

First, the age polynomial terms confirm that earnings follow the standard concave life-cycle profile for most degree groups. Age term enters positively, reflecting early-career income growth, while the squared term is negative, capturing the slowdown and eventual decline as individuals approach retirement.

Second, the coefficients on family size and marital status generally follow expected signs. Family size is negatively associated with earnings for degree groups, Others, Associate, Bachelor, and Master, with statistical significance, although the effect is relatively small. Marital status exhibits a positive association with earnings for most degrees, consistent with both household specialization and selection effects commonly documented in the labor literature.

Third, the gender coefficient shows a persistent and statistically significant earnings gap between men and women across almost all education groups.

Last, the birth cohort fixed-effect F-statistics confirm that birth cohort explains a significant portion of income variation within each degree group. This validates the empirical motivation for explicitly controlling for cohort-level heterogeneity when constructing earnings profiles.

Table VI: Labor Income Risk Decomposition - Full Panel, Aggregate

Component	**Others**	**Associate**	**Bachelor**	**Master**	**Doctoral**	**Law**	**Medical**
Total Risk (σ_η,%)	18.50	17.65	17.14	13.90	19.54	20.08	24.27
Permanent Risk (σ_u, %)	13.22	10.28	11.65	11.72	11.70	15.57	13.88
Transitory Risk (σ_ε, %)	12.93	14.23	12.69	7.63	15.64	12.72	19.90

Table VI summarizes the estimated labor income risks. The total risk (σ_η) at the aggregate level follows:

$$\text{Master} < \text{Bachelor} < \text{Associate} < \text{Others} < \text{Doctoral} < \text{Law} < \text{Medical}.$$

This ranking indicates that Master's degree holders exhibit the greatest resilience to both long- and short-term shocks, whereas Law and Medical face the highest overall risk, which is consistent with their labor earning profiles and greater exposure to persistent and transitory income variability.

Figure III: Labor Income Risk - Full Panel

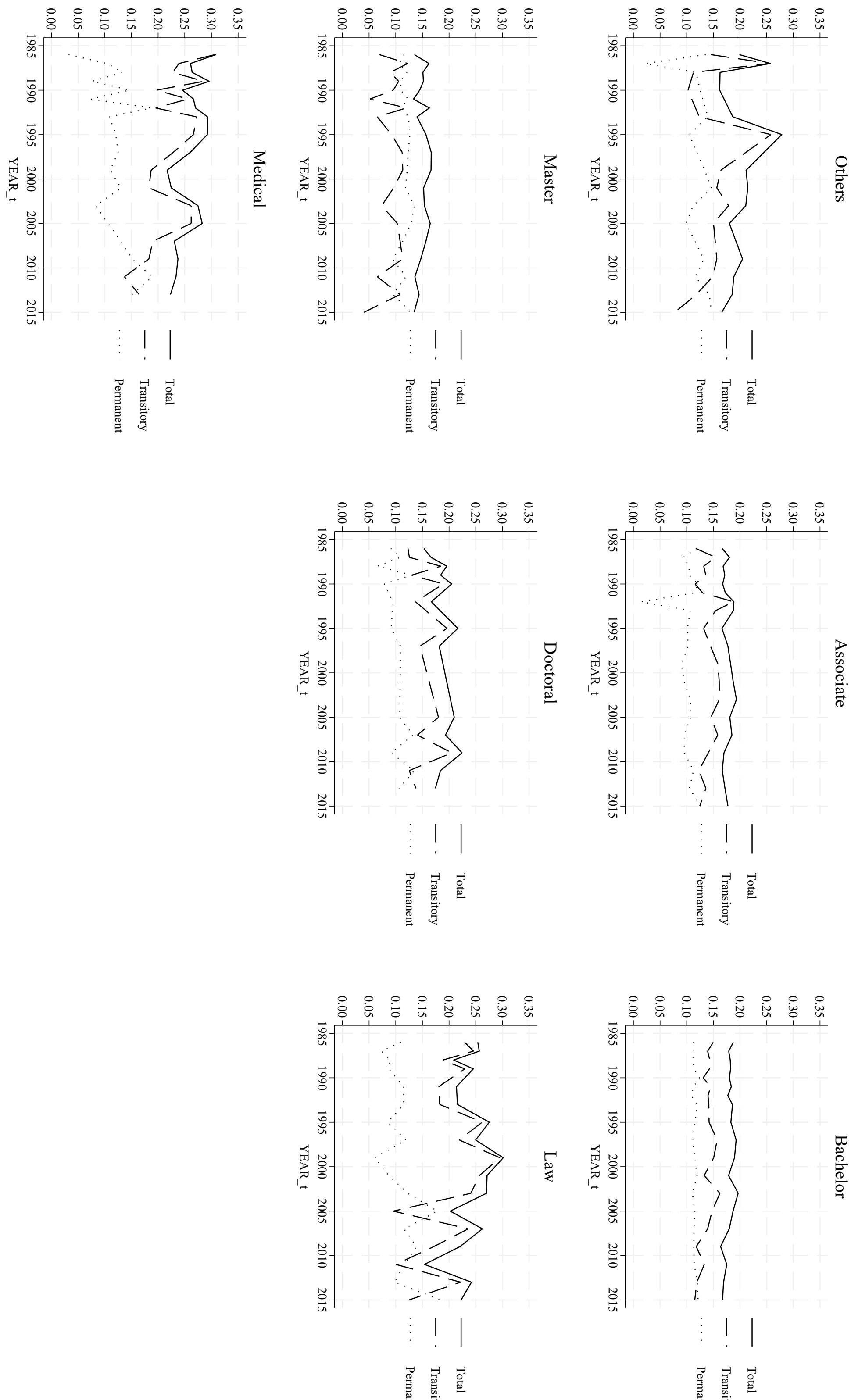


Figure III tabulates the decomposition of labor income risk over 1985-2015, visualizing clear heterogeneity across education groups. Others, Doctoral, Medical, and Law degrees display in relative terms more volatile total, permanent, and transitory risk profiles over time, with frequent year-to-year fluctuations. Associate, Bachelor's, and Master's degrees exhibit comparatively stable and smoother risk paths across the entire sample period.

Looking at the aggregate level, permanent labor income risk, measured by the standard deviation of persistent income shocks, follows a different order. The ranking for permanent risk (σ_u) from the most stable to the most risky long-term income path is:

$$\text{Associate} < \text{Bachelor} < \text{Doctoral} \approx \text{Master} < \text{Others} < \text{Medical} < \text{Law}.$$

Permanent risk ranges from approximately 10.28% for Associate's degree holders to about 15.57% for Law graduates. Bachelor's, Master's, and Doctoral degree holders lie in a relatively narrow band between 11.65% and 11.72%. The most stable long-run earnings profiles, therefore, are for Associates, while Law and Medical degree holders face the greatest exposure to persistent income shocks despite their higher average lifetime earnings.

Transitory risk, measured by the standard deviation of short-term income fluctuations (σ_ε), from the most stable to the most volatile short-run income patterns follows:

$$\text{Master} < \text{Bachelor} \approx \text{Law} < \text{Others} < \text{Associate} < \text{Doctoral} < \text{Medical}.$$

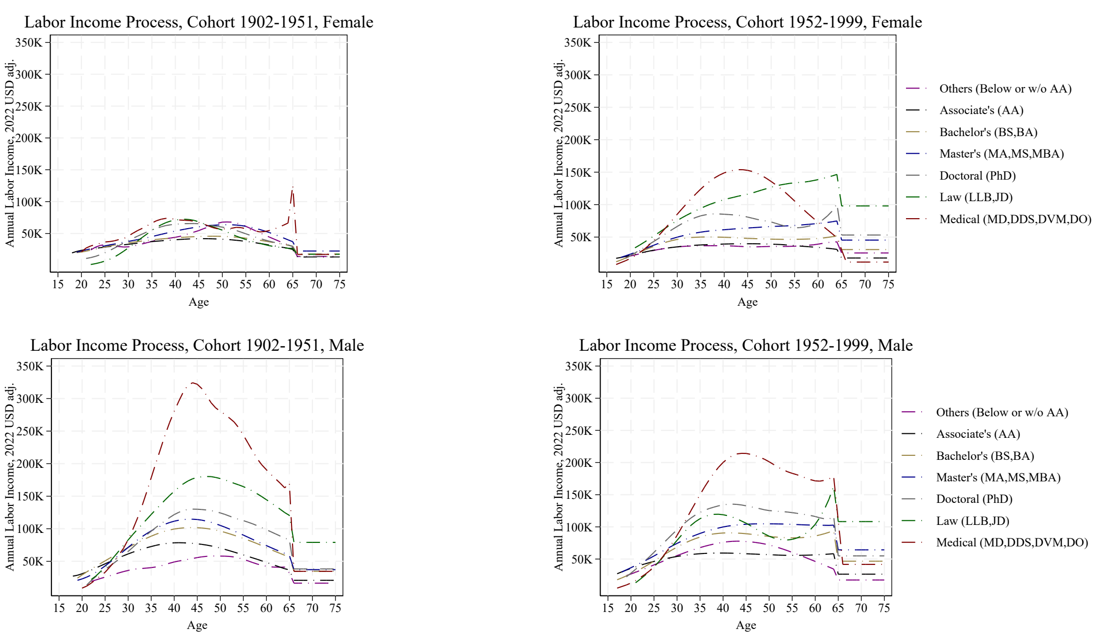
Master's degree holders display the lowest transitory risk at roughly 7.63%, followed by Bachelor's and Law, around 12.70%. Medical and Doctoral degree holders experience the highest short-term risks, which are 19.90% and 15.64%, respectively, suggesting year-to-year labor income uncertainty in these high-skill professions.

Together, the permanent and transitory components address to different dimensions of economic uncertainty. Transitory shocks mainly affect short-run liquidity and can typically be smoothed with savings or temporary adjustments. Permanent shocks, however, shift expected lifetime earnings and have long-lasting effects on personal wealth accumulation. Consequently, education tracks associated with higher permanent risk, such as Law, Medical, and some Doctoral fields, may carry greater long-term earnings uncertainty, whereas degrees like Associate or Bachelor, with relatively low permanent risk, provide more stable lifetime income paths even if short-run fluctuations are present.

V.4. Cohort and Gender Differences

Beyond the aggregate education-based heterogeneity, a further examination by cohort and gender provides additional insights. In the previous subsection, Figure I and Figure II presented the labor income process and human capital profiles for the full sample. As summarized in Table II and Table III, the dataset includes birth cohorts from 1902 to 1999 and contains sufficient observations within each gender-cohort subgroup. The number of observations is statistically sufficient to investigate whether structural shifts have occurred by comparing across these four groups.

Figure IV: Labor Income Process - Gender and Cohorts



To ensure a complete working-life profile at each age in the subgroups, birth cohorts are grouped into two broader categories: an early cohort (1902-1951) and a late cohort (1952-1999).

A closer examination of gender differences across cohorts in Figure IV visualizes huge structural shifts in labor income dynamics over time. In the early cohort, males consistently earned more than females at every education level. This pattern reflects well-documented historical norms in the United States: female labor participation remained limited before the mid-twentieth century, and women's earnings were often heavily constrained by both occupational segregation and social norms. The female labor income profiles for the early cohort are extremely compressed, with low and flat age-earnings trajectories and peak incomes that lie well below those of men born in the same period.

By contrast, early-cohort males display steady and well-defined labor income profiles, with peak earnings exceeding \$300K for Medical degrees and well above \$150K for Law degrees. Their labor income hierarchy closely mirrors the aggregate ranking observed in Figure I:

$$\text{Medical} > \text{Law} > \text{Doctoral} > \text{Master} > \text{Bachelor} > \text{Associate} > \text{Others}.$$

An extreme example can be illustrated with a male from the early cohort with a Bachelor's degree could reach peak annual earnings near \$100K, while early-cohort females, even with the most advanced degrees, can rarely exceed \$80K, regardless of what type of education she have attained.

However, substantial changes appear when turning to the later cohort. Gender gaps has narrowed a lot, and for several degrees the male and female profiles lie much closer together than before. At higher education levels, female Law degree holders in the later cohort exhibit a notably non-concave trajectory, with mid-career earnings that exceed those of their male counterparts. Male Law degree holders do, however, display a sharper rise in earnings after age 55, a pattern absent in earlier cohorts, possibly reflecting structural changes in senior legal careers, such as expanded opportunities for consultancy or flexible practice arrangements.

For Medical degrees, males in the later cohort continue to earn more on average, with the gender gap narrowing substantially. While male Medical degree holders peak above \$200K, females in the later cohort reach peaks above \$150K, which is much higher than in the early cohort. Across the remaining degrees (Doctoral, Master's, Bachelor's, Associate, and Others), men still exhibit earning advantages over women, but the relative gaps are far smaller than in the early cohort.

A final observation is the noticeable decline in peak labor incomes for men across cohorts. Male Medical degree holders fall from peaks above $300K in the early cohort to below $230K in the later cohort, and male Law degree holders drop from around $175K to roughly $125K. These patterns suggest evidence of degree depreciation for high-earning professional fields, potentially driven by changing market structures, increased competition, or shifts in occupational demand. Taken together, these results indicate that while gender convergence in earnings has improved remarkably over time, gender disparities still exist.

Figure V: Human Capital - Gender and Cohorts

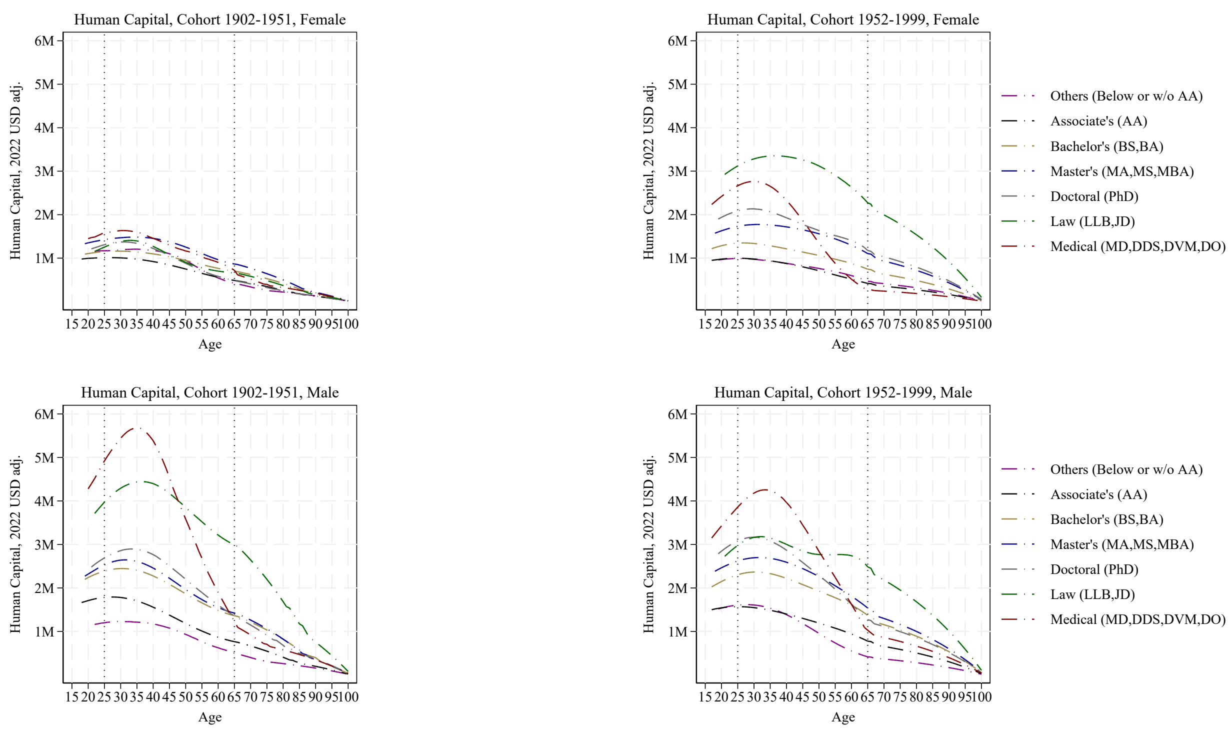


Figure V presents the human capital profiles for females and males across the early cohort (1902-1951) and the later cohort (1952-1999). These patterns broadly mirror the labor income trajectories documented in Figure IV but also provide additional insight into lifetime earnings potential and the expected present value of future labor income.

In the early cohort, female human capital levels are in a very low range, tightly compressed across all degrees. Peak human capital rarely exceeds $1.8 million, even for Medical and Law degrees, reflecting the limited labor market gains and severely constrained long-run earnings opportunities available to women born in the first half of the twentieth century. Differences across education groups are modest, and the human capital hierarchy is fairly flat among all degrees.

However, early-cohort males exhibit substantially higher human capital accumulation, with Medical and Law degrees peaking above \$4 million and other advanced degrees reaching between \$2 million and \$3 million. The gap between early-cohort male and female is therefore extremely large, not only in annual labor income but also in life-cycle wealth generation, with men enjoying more than two to four times the human capital of women at equivalent advanced degree levels.

When examining the later cohort, female human capital profiles rise and expand substantially in magnitude, especially for higher degrees. Female Medical, Law, and Doctoral degree holders now peak between \$2 million and \$3.5 million, more than doubling the levels observed before. The shape of their human capital curves also becomes more concave and career-like, reflecting greater attachment to the labor market, higher lifetime earnings, and increased returns to education. Females with a Law degree achieve the highest human capital among all female degree holders. Then ranking for females in the early to middle working age follows:

$$\text{Law} > \text{Medical} > \text{Doctoral} > \text{Master} > \text{Bachelor} > \text{Associate} \approx \text{Others}.$$

Despite these improvements, males in the later cohort continue to display higher human capital across all degrees. However, the gender gap narrows significantly, with females still trailing males by around \$400K to \$800K at peak with equivalent advanced degrees, but the relative differences are far smaller than in the early cohort.

Another generational shift observed is the decline in human capital peaks for later-cohort males, especially among Medical and Law degree holders. Medical human capital falls from well above \$5 million in the early cohort to roughly \$4.2 million in the later cohort, while Law declines from around \$4.5 million to near \$3 million. These declines are consistent with the reduction in the highest male labor incomes documented in Figure IV, suggesting that changes in the structure of the labor market, occupational demand, or wage premium have contributed to a form of degree depreciation in high-earning professional fields.

Table VII: Labor Income Risks by Cohort, Gender, and Education Degree

Samples	**Others**	**Associate**	**Bachelor**	**Master**	**Doctoral**	**Law**	**Medical**
Total Annual Risk (σ_η, %)							
1902–1951, Female	19.64	18.25	18.28	14.88	18.65	23.51	26.75
1952–1999, Female	17.40	17.77	18.16	15.55	23.95	21.42	23.89
1902–1951, Male	20.32	16.95	17.73	14.42	18.11	25.15	25.12
1952–1999, Male	20.64	17.78	18.18	14.90	14.77	23.48	25.37
Permanent Risk (σ_u, %)							
1902–1951, Female	10.48	11.58	12.65	12.30	11.03	10.72	12.40
1952–1999, Female	11.70	9.88	11.41	11.46	16.39	10.23	9.53
1902–1951, Male	11.05	10.22	11.19	12.01	8.64	10.37	12.80
1952–1999, Male	12.95	10.34	11.38	10.95	9.02	10.91	12.08
Transitory Risk (σ_ε, %)							
1902–1951, Female	16.61	14.11	13.20	8.37	15.04	20.93	23.70
1952–1999, Female	12.88	14.77	14.12	10.51	17.47	18.82	21.65
1902–1951, Male	17.16	13.52	13.76	7.99	15.91	22.92	21.62
1952–1999, Male	16.06	14.46	14.18	10.11	11.70	20.79	22.31

Furthermore, the labor income risks decomposition for these four groups exhibit interesting patterns, according to Table VII. At the aggregate level, Medical and Law consistently rank with very high-level total risk and transitory income risk. Master maintains low, moderate, stable profiles across permanent and transitory components, reinforcing the earlier observation that these groups experience smoother earnings paths.

Based on the availability of the data, Figure A1 to Figure A4 in the Appendix illustrates how labor income risks vary across 1985-2015. Over generations, transitory risk increases in Associate, Bachelor, and Master for all genders, Medical and Law experience very big transitory shocks, while Master has the lowest transitory risk amongst all. Doctoral males face much lower transitory risk than before, while maintaining the lowest permanent risk. The permanent risk is consistently smaller than the transitory risk, except for Master. Law experiences the second lowest permanent risks, while Doctoral females experience the highest permanent risks.

Early-born females (See Appendix Figure A3) with Bachelor's degrees show stable and non-volatile risk profiles, and similar stability appears for Associates and Master's, though the balance between permanent and transitory components differs: Master's faces larger permanent risk, whereas Associates carry comparatively higher transitory risk. Early-born females in Others, Doctoral's, Law, and Medical, sometimes exhibit higher total risk, exceeding 25% at times, but relatively lower transitory risk. Doctoral females experience elevated transitory risk in the early 2010s, while Medical and Law females display declining transitory risk since the 2000s.

Among later-born females (See Appendix Figure A4), Associate, Bachelor, and Master degree holders continue to show stable risk profiles, though transitory risk rises for Master in the later cohort. Later-born females with Doctoral degrees face higher risks during the 1990s to early 2000s. For Others, Law, and Medical, later-born females record lower total risk in the 1990s and early 2000s, with notably low transitory risk for Others and Law, while Medical degrees show the lowest permanent risk among these categories.

Later-born males (See Appendix Figure A2) with Associate, Bachelor's, and Master's degrees maintain similarly stable profiles, with higher transitory risk for Master's in the later cohort, mirroring the pattern observed in females. Later-born males in Others experience higher transitory and total risk between 1995 and 2005 than their early-born counterparts. For Doctoral degrees, later-born males generally show reduced total and transitory risks compared to early-born males (See Appendix Figure A1). Meanwhile, later-born males in Law and Medical degrees experience risk levels comparable to those of the early-born male group.

From Appendix Figure A5 and Figure A6, the aggregate level comparison between early- and later-born cohorts without gender specifications also exhibits a significant degree of depreciation in the earnings and human capital magnitudes.

Table A1 to Table A4 in the Appendix show how cohort and gender shape the labor income process. For both early- and later-born males, labor earnings are largely insensitive to family size, with almost all Family Size coefficients statistically insignificant. The effects of marriage are mostly positive and statistically significant, though they decrease in magnitude over generations. Female labor earnings display a consistently negative and statistically significant relationship with Family Size across generations. The marital status becomes positive and significant for Others, Associate, Bachelor, and Master.

Overall, the regression results indicate that women's earnings, specifically for those with midto high-level educational attainment, remain more elastic to family circumstances than men's, whose earnings are less affected by household sizes and positively associated with marriage status.

V.5. Discussion and Limitation

The empirical evidence suggests that, yes, degree depreciation is happening, and generational cohort effects and heterogeneity of education returns are confirmed. These patterns may reflect broader structural changes, including evolving labor market conditions, shifting returns to higher education, and differences in retirement security across generations. While data limitations prevent a full identification of delayed workforce entry, behavioral changes, or shifts in societal values such as labor rights and gender equality, empirical evidence suggests that people nowadays face a new reality characterized by reduced peak income and generally lower wealth accumulation paths.

From the perspective of educational attainment, higher education continues to yield economic benefits; however, the magnitude and persistence of these returns appear more uncertain as income risks remain high. The gap in returns across advanced degrees may reflect structural saturation in the labor market, where additional schooling no longer guarantees proportionately higher earnings. Moreover, the relationship between education and labor income has become more complex and context-dependent than the traditional *higher the education, higher the income* narrative.

However, while the EDUDEGREE variable groups individuals into broad educational categories (see Table A5), the underlying sub-degree credentials can differ substantially in field of study, industry placement, and career trajectory. For example, "Doctoral" (PhD) is generalized without any detailed segmentation, yet in reality a PhD in the arts differs considerably from a PhD in mathematics or in management. Similarly, within the Medical category, dentistry differs from veterinary medicine, general medicine, or osteopathy. In Law, the JD and LLB represent different degree structures and areas of focus. These within-degree differences may be large enough to generate meaningful heterogeneity in labor market outcomes. Due to the lack of detailed segmentation, some of the generalized implications may not fully capture the true variation in labor income patterns across more specific fields.

Similarly, the analysis does not distinguish between detailed employment industries or occupational codes (e.g., technology, finance, business, healthcare, or education sectors), which could explain some of the observed variation in income trajectories across degrees. Nor does it incorporate race, ethnicity, or state-level differences, all of which are known to play important roles in income distribution and career mobility within the U.S. context. In addition, while pre-processing the dataset to better illustrate labor income trajectories, individuals with missing data or non-full-time employment observations were dropped, and the regression does not account for those who earned non-U.S. degrees. As a result, the analysis may not fully reflect the broader labor force, since individuals often experience employment gaps or transitions between full-time and part-time work. Furthermore, because the data are based solely on the U.S. labor market, the results may not generalize directly to other economies, particularly European systems where wage structures, labor protections, and education costs differ significantly. Future research could extend this analysis through cross-country comparisons or by incorporating industry-level and occupational codes to better capture labor market segmentation and structural heterogeneity.

From a policy and individual decision-making perspective, these findings also carry an important message about the cost-benefit trade-off of higher education. In the U.S. context, where tuition fees represent a substantial financial investment, the results can serve as a reference for individuals considering advanced academic pursuits. The sunk costs associated with tuition, time, and opportunity make it an expensive investment that must be weighed against the actual economic return over the life cycle. However, education systems in many European countries involve lower or subsidized tuition, which might alter the trade-off and lead to different patterns of degree returns. Local students have less financial stress comparatively. For international students facing both tuition costs and relocation expenses, the heterogeneity in degree returns could be even more severe in real life, raising important questions about whether the economic payoff justifies the cost, particularly for those planning to work in the country of their study.

Overall, the empirical results suggest a labor market in transition, one in which traditional expectations about education, earnings, and career security are being reshaped by generational change, the development of gender equality, occupational heterogeneity, and evolving economic conditions. Future studies would be meaningful as persistent structural barriers and transitory fluctuations continue to shape labor income dynamics.

VI. Conclusion

In conclusion, the thesis study evaluates whether degree depreciation is happening by examining the heterogeneity of education returns measured by the labor income process and human capital trajectories over the individual life cycle. The results confirm changes across generations: post-secondary education degrees continue to associate positively with labor earnings and personal wealth accumulation, but the economic value of higher education degrees has become more compressed and less differentiated over time. In other words, degree depreciation is happening.

Across all seven degrees available in the PSID-SHELF dataset, the marginal difference between adjacent degree levels has narrowed significantly, suggesting diminishing returns to additional schooling. This reflects a labor market in which further education no longer guarantees proportionately higher income, a pattern that used to be significant for people born in the early half of the twentieth century, especially for males.

Labor income risk decomposition also exhibits great heterogeneity across degrees. While the labor income curves and human capital curves become compressed and shrink in value, most labor income risk levels, however, do not experience a large decline in magnitude. Transitory risks are generally larger than the persistent risks, except for Master's. Educational degrees, while following a conventional perception hierarchy, not only serve as pathways to higher earnings but also as mechanisms that allocate individuals into careers with distinct risk profiles. This implies an important trade-off between magnitude and stability: high-income careers such as Medical and Law offer substantial short-term rewards and long-term opportunities but are also characterized by greater exposure to income fluctuations, whereas mid-tier degrees such as Bachelor's and Master's tend to generate smoother and more stable wealth accumulation over the life cycle.

Cohort comparisons provide a generational dimension to these patterns. Individuals born between 1902-1951 exhibit higher income peaks and greater lifetime wealth accumulation compared to those born after 1952. Later cohorts, despite benefiting from broader access to higher education, face a new economic reality characterized by lower income peaks, slower accumulation, and smaller lifetime returns. This shift likely reflects structural changes in labor markets, including rising education costs, slower wage growth, and more competitive job environments, reducing the payoff of higher education over time.

Gender differences add another important dimension. Males historically maintained higher incomes across all education levels, particularly among earlier cohorts. However, this gap has narrowed significantly among later generations, reflecting progress in female labor participation and societal shifts toward gender equality. Still, regression evidence indicates that women's labor earnings remain more elastic to family structure, particularly household size and marital status, while men's income is less affected by such factors. This persistent asymmetry suggests that underlying structural barriers continue to shape gender-relevant income patterns even as average gaps narrow.

It is also important to note that the dataset ends in 2019, meaning that the analysis does not capture the post-pandemic labor market transformation. It would be particularly interesting to study those evolving patterns once additional longitudinal data become available, as recent documentation suggests that unemployment rates for recent graduates have remained persistently higher, and the pandemic may have reshaped both wage trajectories and perceptions of higher education investment. Future data waves will be crucial for understanding whether or how these disruptions permanently or temporarily alter income trajectories across cohorts and degrees.

Taken together, the findings offer a comprehensive perspective on degree depreciation in the U.S. labor market. The returns to education, measured through labor income dynamics, have become increasingly heterogeneous, varying by degree type, gender, and cohort. Post-secondary degrees continue to convey labor market advantages relative to secondary or non-degree holders, but the economic benefits and overall worthiness of higher education have become increasingly dependent on how individuals evaluate the trade-offs between cost, stability, and long-term earnings potential. As new birth cohorts enter a fast-evolving labor market, understanding these dynamics will be crucial for policymakers, institutions, and individuals seeking to plan educational investments and align expectations with the realities of a challenging global economy. Future research should also move beyond education and consider broader labor-market forces, such as unemployment dynamics, mobility, immigrant integration, ethnic and geographic disparities, and demographic shifts, to better understand how education translates into economic opportunity.

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Appendix

Acknowledgment: Use of Artificial Intelligence Tools

This thesis made limited use of artificial intelligence (AI) tools as support during the research and writing process.

Microsoft Copilot was used to assist in the construction and refinement of simulation code in the Jupyter Notebook file. This related to the construction of a complete and comparable life cycle for all subgroup samples. For example, for individuals observed above the age of 65 who do not have recorded age-extended profiles after 65, missing values from the observed age through age 100 were filled using the estimated post-retirement income level at the 64/65 critical retirement point.

ChatGPT (OpenAI) was used as a supportive tool for debugging Stata code, constructing loops, and performing content checks. This included assistance with grammar, formatting, and clarity of exposition in the Overleaf document.

The use of these tools did not replace independent analytical work but served as a supplementary aid to improve efficiency and code reliability, in accordance with academic integrity guidelines.

Table A1: Labor Income Process – Female, Early Cohort (1902–1951)

Variable	Lowest	Associate	Bachelor	Master	Doctoral	Law	Medical
Dependent variable: $\log(Y_{it})$							
Family Size	-0.2447***	-0.0541***	-0.1372***	-0.0980***	-0.1134	-0.2183	0.3281**
	(4.6798)	(3.2041)	(11.4506)	(5.5476)	(1.3455)	(1.0613)	(2.3088)
Marital Status	0.0868	-0.1071**	-0.0208	0.0065	-0.2716	0.3618	0.0000
	(0.4903)	(2.2626)	(0.6409)	(0.1311)	(1.4191)	(0.8233)	(0.0000)
n	218	1767	5159	2636	285	50	27
T-bar	8.6857	14.5816	17.5628	19.2474	17.0897	21.8537	17.1667
Adjusted R^2	0.3321	0.0733	0.0876	0.1177	0.1258	0.6176	0.5388
F-statistic	16.1979***	23.7303***	72.9330***	50.5343***	4.8750**	5.6463***	4.7548**

Significance: $p < 0.10$ (*) , $p < 0.05$ (**) , $p < 0.01$ (***)

Table A2: Labor Income Process – Female, Later Cohort (1952–1999)

Variable	Lowest	Associate	Bachelor	Master	Doctoral	Law	Medical
Dependent variable: $\log(Y_{it})$							
Family Size	-0.0085	-0.1153***	-0.1369***	-0.0885***	0.1172*	-0.0590	-0.0492
	(0.2875)	(12.9690)	(19.4001)	(7.7518)	(2.5956)	(1.7499)	(1.0259)
Marital Status	0.3538***	0.0948***	0.0863***	0.1130***	-0.1523	0.0296	0.0852
	(4.7118)	(4.1009)	(4.6026)	(3.6694)	(1.2583)	(0.3071)	(0.6135)
n	644	6367	14206	4601	313	373	278
T-bar	4.7554	6.0561	6.9471	7.9439	7.3043	9.2556	8.0225
Adjusted R^2	0.1232	0.0673	0.0622	0.0803	0.1798	0.1420	0.3397
F-statistic	7.2628***	71.0032***	176.0006***	71.7339***	9.1251***	10.5210***	21.5791***

Significance: $p < 0.10$ (*) , $p < 0.05$ (**) , $p < 0.01$ (***)

Table A3: Labor Income Process – Male, Early Cohort (1902–1951)

Variable	Lowest	Associate	Bachelor	Master	Doctoral	Law	Medical
Dependent variable: $\log(Y_{it})$							
Family Size	-0.0033	0.0115	-0.0009	0.0131	0.0109	-0.0409	0.1336^{**}
	(0.0417)	(0.8924)	(0.1342)	(1.3939)	(0.4406)	(1.0579)	(2.3505)
Marital Status	-0.5428^{**}	0.1807^{***}	0.2885^{***}	0.2426^{***}	0.5344^{***}	0.3114^{***}	-0.4940^{**}
	(2.1016)	(3.4040)	(9.7369)	(6.4428)	(5.5883)	(2.7815)	(2.3022)
n	125	2587	9955	4342	927	842	454
T-bar	8.6857	14.5816	17.5628	19.2474	17.0897	21.8537	17.1667
Adjusted R^2	0.3454	0.1401	0.1329	0.1729	0.2831	0.1917	0.2517
F-statistic	2.3917^{*}	68.7948^{***}	219.1045^{***}	166.5452^{***}	49.1488^{***}	27.7317^{***}	27.8880^{***}

Significance: $p < 0.10$ (*) , $p < 0.05$ (**) , $p < 0.01$ (***)

Table A4: Labor Income Process – Male, Later Cohort (1952–1999)

Variable	Lowest	Associate	Bachelor	Master	Doctoral	Law	Medical
Dependent variable: $\log(Y_{it})$							
Family Size	-0.0137	0.0143^{*}	0.0186^{***}	0.0016	-0.0584	0.0708	0.0798^{*}
	(0.3612)	(1.7517)	(2.9619)	(0.1223)	(1.4935)	(1.5703)	(1.8435)
Marital Status	0.0520	0.1909^{***}	0.1829^{***}	0.1483^{***}	0.2358	-0.0347	0.0403
	(0.4089)	(6.7266)	(9.2619)	(3.4119)	(1.5522)	(0.2175)	(0.2144)
n	327	4847	14093	3020	347	471	457
T-bar	4.7554	6.0561	6.9471	7.9439	7.3043	9.2556	8.0225
Adjusted R^2	0.1508	0.0739	0.1265	0.1069	0.2745	0.1454	0.2048
F-statistic	5.0225^{***}	46.8579^{***}	330.3504^{***}	56.6858^{***}	10.3165^{***}	12.4401^{***}	19.8800^{***}

Significance: $p < 0.10$ (*) , $p < 0.05$ (**) , $p < 0.01$ (***)

Figure A1: Labor Income Risk - Early-born Male

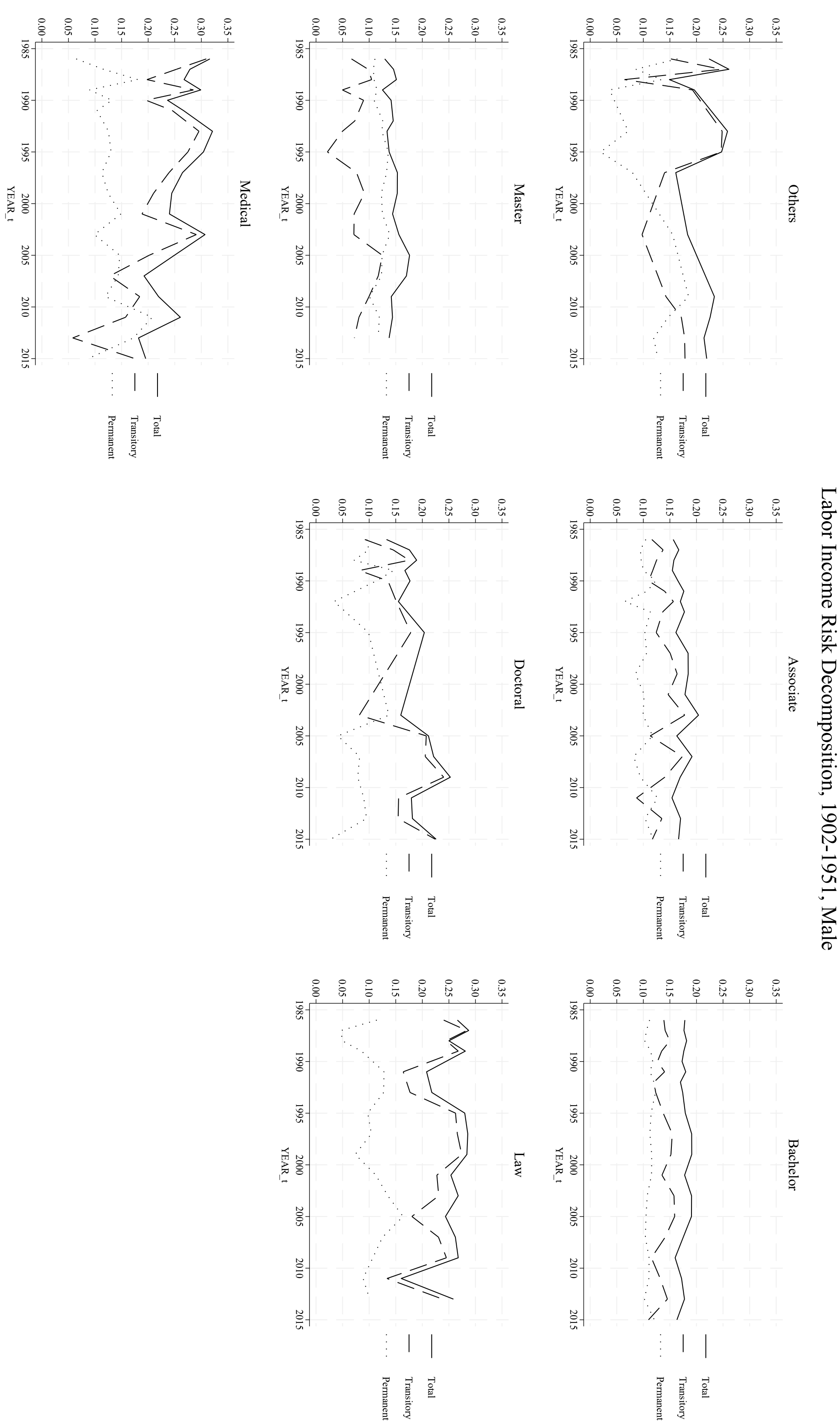

Figure A2: Labor Income Risk - Later-born Male

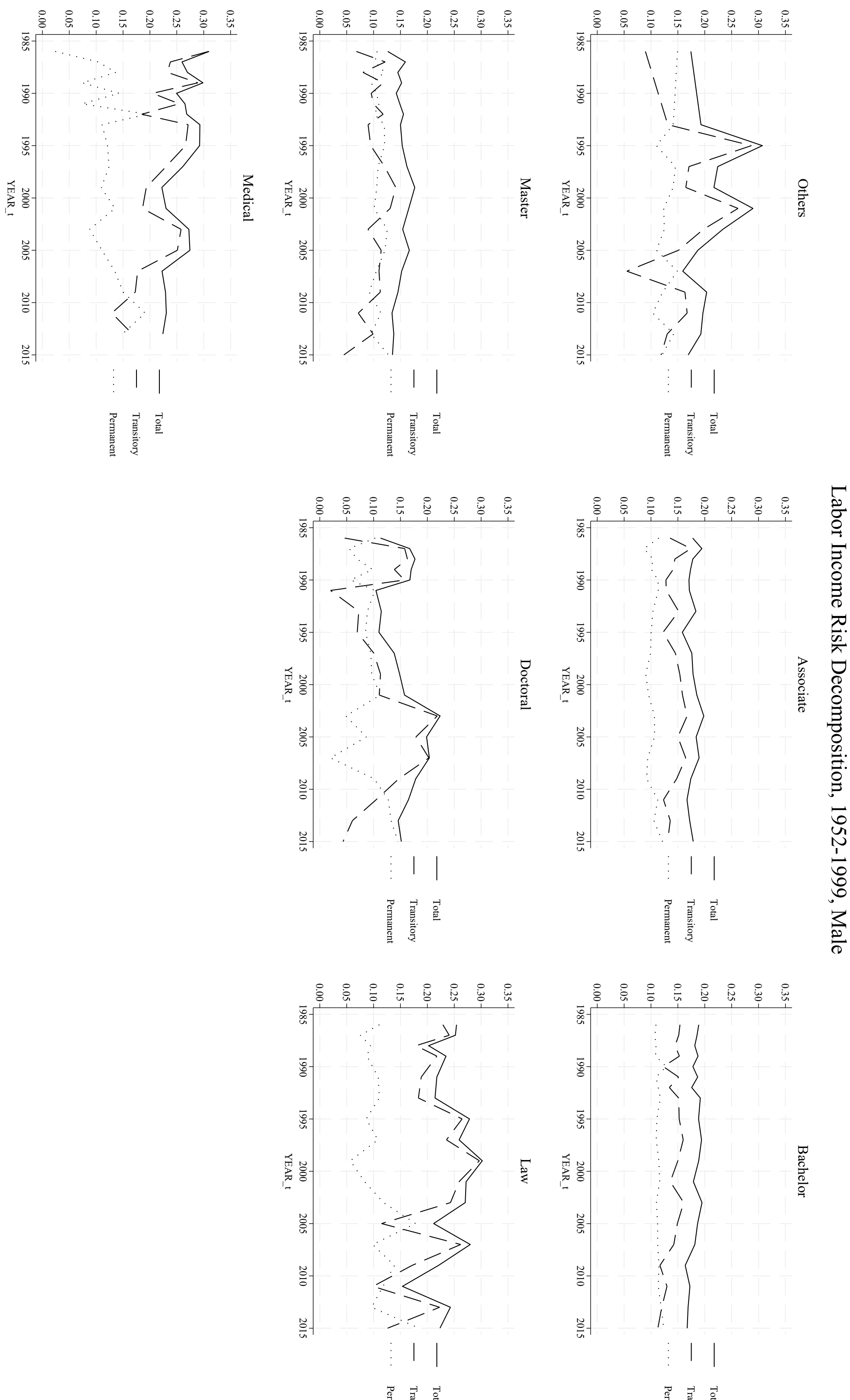

Figure A3: Labor Income Risk - Early-born Female

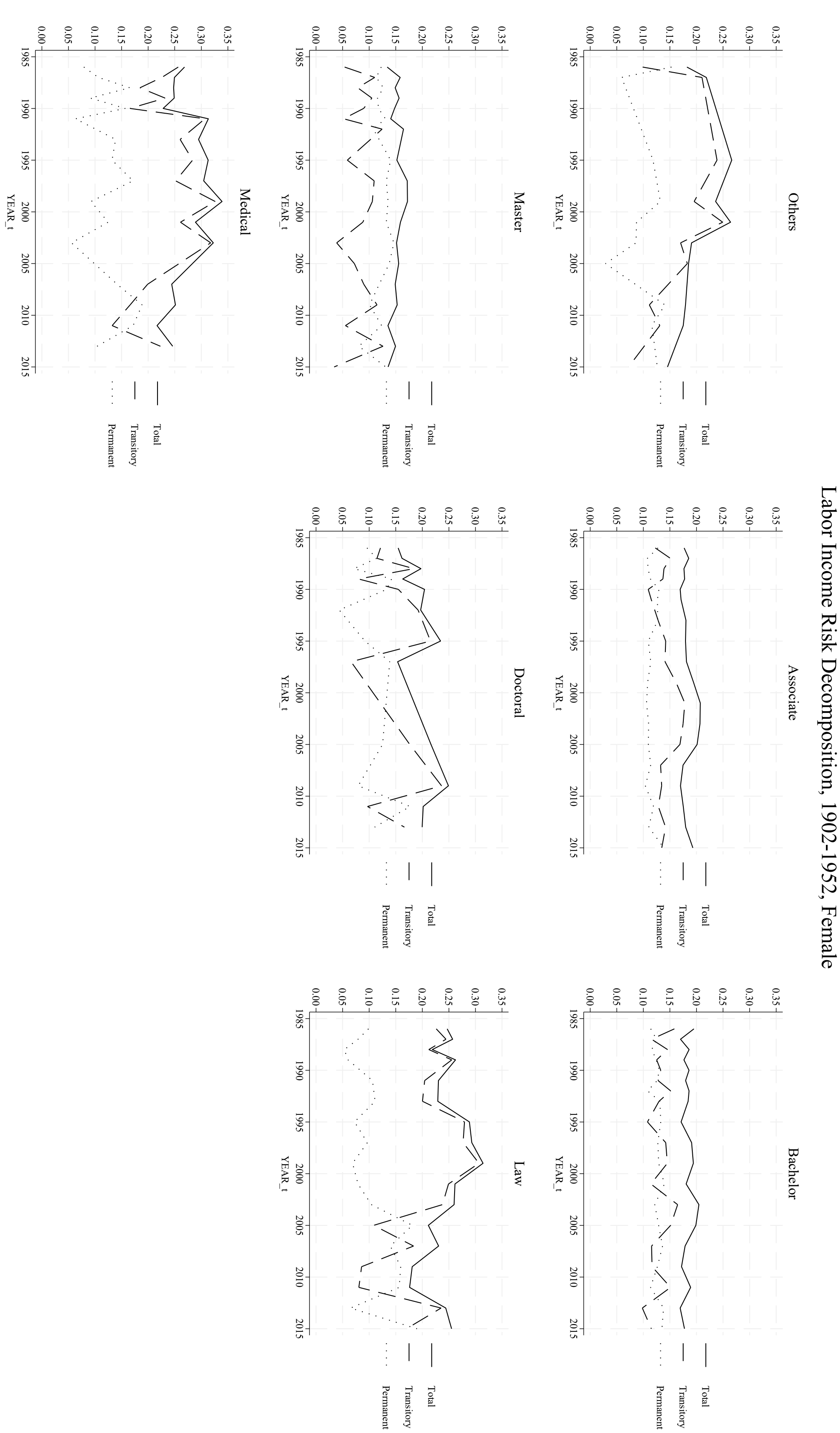

Figure A4: Labor Income Risk - Later-born Female

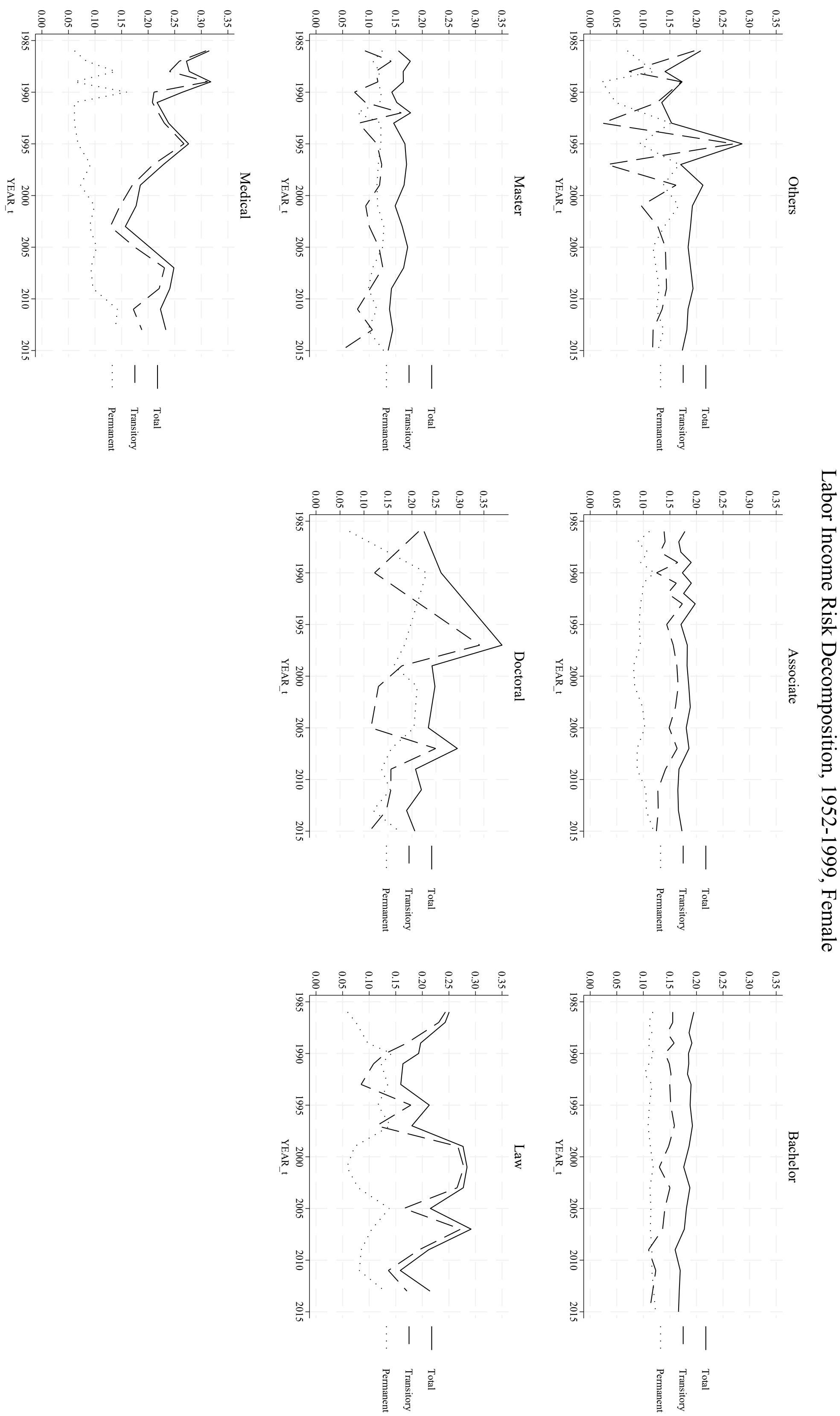

Figure A5: Labor Income Process - Early-borns v.s. Later-borns

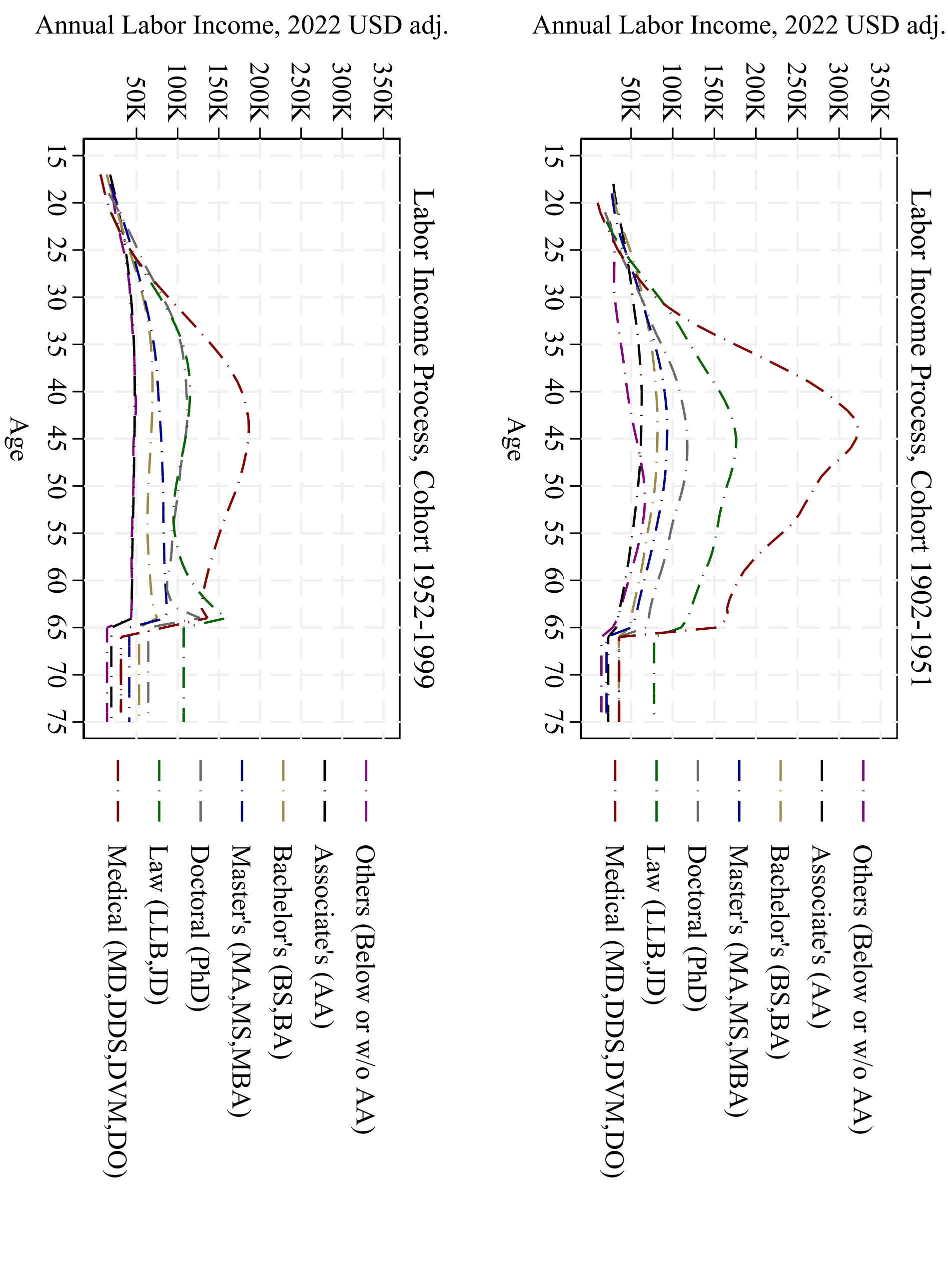

Figure A6: Human Capital - Early-borns v.s. Later-borns

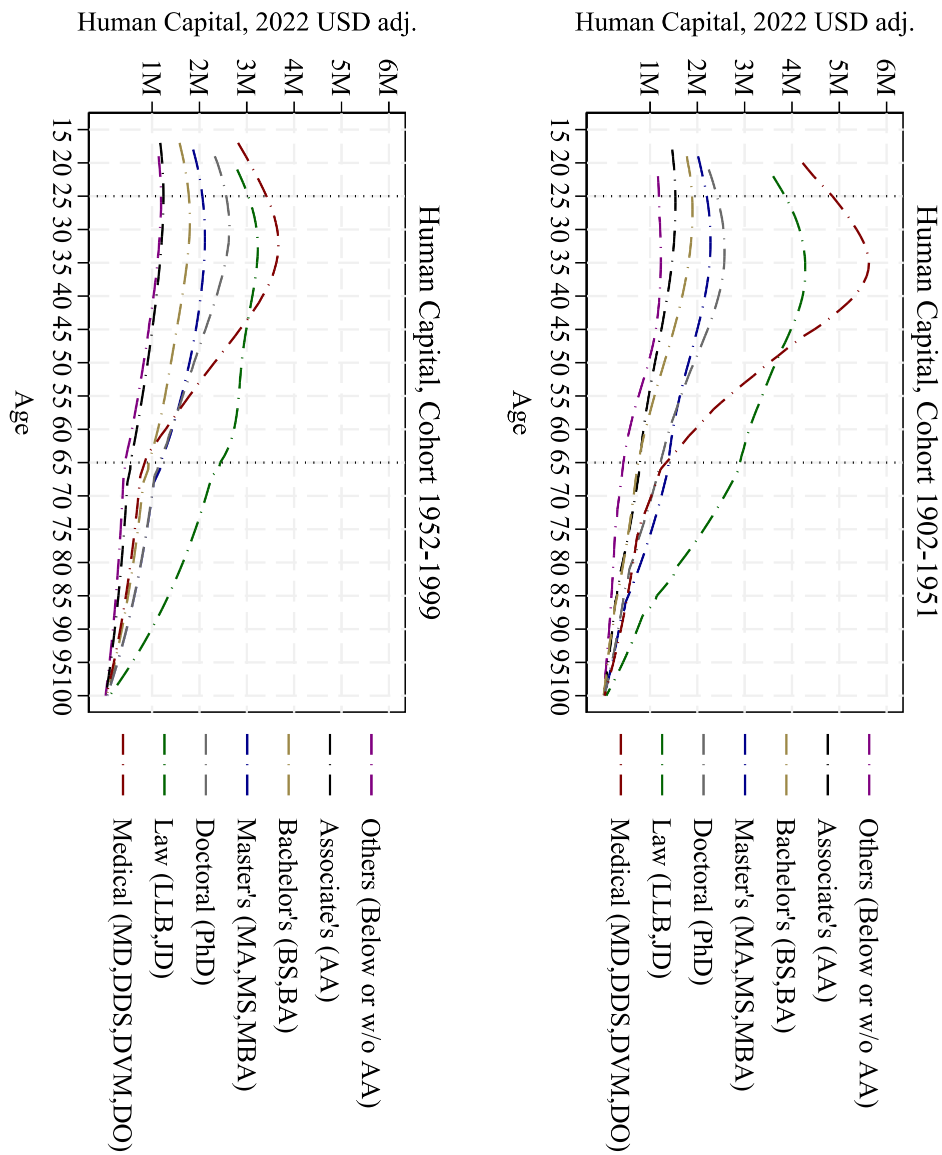

Table A5: PSID EDUDEGREE Categories and Descriptions

Category	**Abbreviation(s)**	**Description**
Others	–	High school diploma, GED, or no post-secondary credential.
Associate’s	AA (A.A., A.S.)	Two-year undergraduate degree, typically awarded by community colleges.
Bachelor’s	BA, BS	Four-year undergraduate degree (Bachelor of Arts or Bachelor of Science).
Master’s	MA, MS, MBA	Graduate-level degree pursued after a bachelor’s.
Doctoral	PhD	Highest academic research degree (Doctor of Philosophy).
Law	LLB, JD	Professional law degree required for attorney licensure.
Medical	MD, DDS, DVM, DO	Professional medical or clinical degrees (medicine, dentistry, veterinary medicine, osteopathy).