The Effects of Tuition Hikes on the Choices of College Majors

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Abstract

The Effects of Tuition Hikes on the Choices of College Majors

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This dissertation includes an introduction, three related chapters, and a summary at the end. The primary objective of this dissertation is to explore the factors that influence college enrollment decisions and examine the impact of financial aid policies on these decisions. The thesis focuses on two distinct fields of study: STEM (Science, Technology, Engineering, and Mathematics) and ARTS (non-STEM fields defined within the thesis). STEM fields are generally associated with higher-paying career opportunities, while ARTS fields are often considered to offer relatively lower-paying career paths.

The introduction section of this dissertation begins by examining historical trends in schooling, with a focus on developed countries, notably the U.S. It discusses significant observations from the past decades, including a notable increase in college enrollment rates, the upward trend in college costs, and the presence of generous student financial aid programs. The introduction also sets the stage by posing several key research questions that will be addressed throughout the dissertation. Central to the research is the main question: How do various financial aid policies influence college enrollment decisions, particularly in the context of STEM and ARTS college majors? With these questions in mind, the introduction also outlines the unique contributions this dissertation aims to make to the existing literature.

The first chapter of this dissertation serves as an extensive literature review on educational choice. It offers an in-depth exploration of various perspectives from which scholars examine the main determinants influencing individuals' educational decisions.

Specifically, the chapter delves into how researchers have modelled schooling decisions, focusing on college enrollment and, more specifically, the college major choices, constituting this dissertation's central theme. Furthermore, this chapter presents various educational policies implemented in the U.S., such as merit-based scholarships and need-based grants.

This chapter explores reduced-form models investigating the relationship between wages and schooling. Next, the chapter introduces the pioneers of structural models, which provide a deeper understanding of the underlying mechanisms driving educational decisions. The discussion then turns to static and dynamic empirical self-selection papers. Another essential strand of literature that this chapter covers is the research that focuses on resolving uncertainty about individuals' tastes and abilities. Furthermore, the chapter deeply examines the subjective expectations data framework. Researchers in this field use datasets designed to elicit individuals' expectations about future outcomes.

The first chapter also delves into historical trends in U.S. college attainments and wage premiums in the twentieth century. This chapter discusses the existing research that explains changes in the mean ability of different educational groups over time. Furthermore, the chapter explores how college attendance patterns have reversed over time, specifically examining the role played by family income and academic ability before and after World War II. Another focus aspect of this chapter is the puzzle of the higher trend of college wage premiums compared to the lower rates in college enrollment over the past decades. The literature on the determinants of college or college major choices is categorized, encompassing monetary and non-monetary factors influencing educational decisions. Additionally, the chapter explains studies investigating the impact of various financial aid policies on college enrollment rates. The chapter concludes by describing various educational policy experiments conducted in the U.S. over the past decades.

The second chapter of this dissertation focuses on establishing crucial empirical facts about working individuals in the U.S. economy. These facts will serve as essential inputs for calibrating the life cycle model presented in the following chapter. The information of interest includes income life cycle statistics such as mean, mean/median, and Gini coefficients.

These statistics will be derived from the Panel Study of Income Dynamics (PSID) for the survey years 1968-2019. They are vital for mapping the life cycle model to real-world data and finding the relevant distributional moments of the benchmark model economy. These moments are means, standard deviations and cross-correlations of three initial endowments of agents after graduation from high school (learning ability, the initial stock of human capital and the initial assets). Moreover, the chapter estimates the skill price growth rates and human capital depreciation rates for three educational categories. I obtained the growth rates of skill prices equal to 0.53%, 0.35%, and -0.13% and depreciation rates of human capital as 0.9%, 0.6%, and 0.0% for STEM, ARTS, and no-college individuals, respectively.

Chapter three of this dissertation employs a heterogeneous life cycle, a human capital model, solved using dynamic programming techniques and fitted to the sample data from the PSID. The results from this chapter reveal essential insights into the characteristics of college students and their comparative advantage in learning abilities. Specifically, the analysis shows that, on average, college students have higher learning abilities, allowing them to acquire human capital more efficiently. This comparative advantage in learning ability enables them to accumulate higher levels of human capital, which will receive higher skill prices in the labour market, leading to better career prospects. As a result, college students, especially those in STEM fields, enjoy higher wages, earnings, and consumption paths compared to individuals who do not choose to go to college.

Chapter three presents ten policy experiments based on the real-life education policies discussed. These experiments investigate the potential impact of different policy interventions on college enrollment and major choices. The policy experiments include a 30% increase in merit-based scholarships, a 30% increase in need-based grants, a 30% reduction in tuition and fees, a 35% increase in federal loan limits, three extensions to the merit-based scholarship policy, and three modifications in the need-based grants policy. The extensions entail expanding the maximum aid amount to more eligible agents, extending the financial aid coverage to more individuals, or both.

Among the various policies examined, the reduction in tuition and fees stands out as the most effective in increasing overall college enrollment and enrollment in STEM and ARTS fields. This policy significantly increases 9.9 percentage points for college enrollment, 0.3 percentage points for STEM enrollment, and 9.6 percentage points for ARTS enrollment. However, despite its effectiveness, the reduction in tuition and fees is not considered cost-efficient. This policy distributes financial aid broadly among all individuals without targeting specific subgroups. This result allows for exploring alternative approaches for increasing college or major-specific enrollments.

The results also underscore the superiority of policies that directly and precisely focus on specific groups of individuals instead of policies lacking a distinct target group. For instance, one highly effective and efficient experiment entails extending the eligibility for merit-based financial aid and expanding the maximum scholarship amount concurrently. This policy substantially increases college enrollment by 5.4 percentage points, demonstrating both efficacy and efficiency. Remarkably, it boosts \$4.7 in the present value of students' lifetime earnings for each additional dollar allocated to this financial aid policy experiment. Another approach that targets low-asset individuals and extends full tuition and fees coverage to a broader range of eligible individuals results in a high increase of 5.3 percentage points in college enrollment. Nonetheless, the efficiency of this policy stands at \$3.3, which is lower than a less effective policy that entails widening the threshold for receiving need-based grants. Despite its relatively modest 1.5% increase in college enrollment, this less-effective policy exhibits higher efficiency, that is, \$4.3. These findings highlight the importance of effectiveness and efficiency in addressing financial barriers low-income students face.

By identifying the most effective and efficient financial aid policies, this chapter provides crucial insights for policymakers aiming to promote college access and major choices. The findings highlight the importance of targeting specific subgroups and tailoring financial aid strategies to achieve the desired outcomes in college enrollment and major decisions.

Keywords: Human capital accumulation; Comparative advantage; College, STEM, and ARTS enrollments; Tuition hike; Financial aid policies; Dynamic programming; Simulated annealing method.

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Introduction

This section introduces the main topics and themes explored in the subsequent chapters. It starts by illustrating the historical trends in college enrollment and tuition, offering a comprehensive overview of how these factors have evolved. Next, it aims to motivate the reader by presenting the relevant research questions addressed throughout the thesis. These research questions are carefully chosen to investigate the dynamics and factors influencing individuals' choices regarding college enrollment. Finally, I will specify the unique contributions of this thesis to the existing educational choice literature. By conducting in-depth analyses, incorporating relevant data, and employing advanced modelling techniques, my research aims to add new insights and perspectives to the field.

Schooling decisions

College enrollment has experienced a significant increase in recent decades. Data from the Organisation for Economic Co-operation and Development (OECD) reveals that many young adults (aged 25-34) in developed countries pursue postsecondary education. On average, across OECD countries, the proportion of younger adults with some years of postsecondary education has risen from 73.5% in 1998 to 86.1% in 2020.[1]

Figure 1 depicts the college and university enrollment rates in the United States since the early 1970s. Over this period, the overall enrollment rate for individuals aged 18 to 24 has significantly risen, climbing from 24 percent in 1973 to 40 percent in 2020.

[1] Source: OECD, Population with tertiary education, (last accessed December 2023).

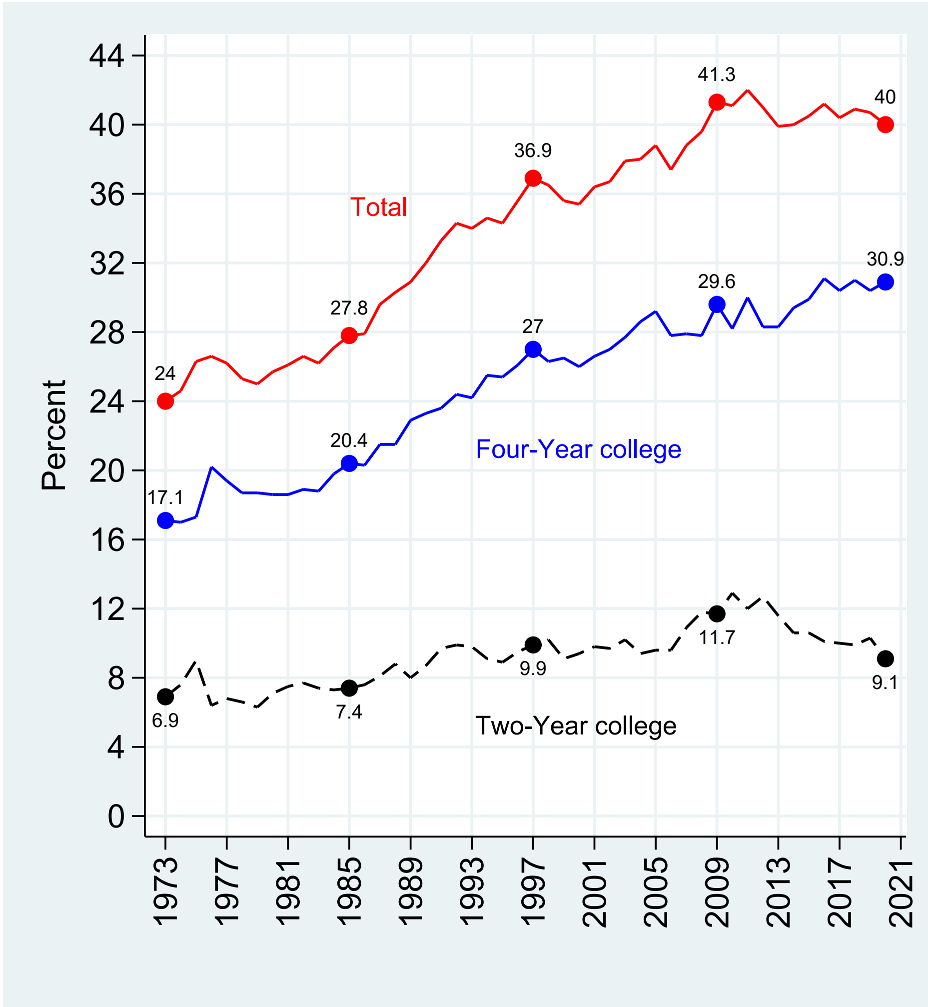

Figure 1: Percentage of 18- to 24-year-old individuals enrolled in college, 1973 through 2020

Furthermore, as illustrated in Figure 1, the data demonstrates that the college enrollment rate for four-year colleges and universities has consistently surpassed that of two-year institutions over the past few decades. Comparing the two, the enrollment rate for four-year colleges has experienced a more significant increase. In the early 1970s, the enrollment rate for four-year colleges stood at 17.1 percent, while in 2020, it reached 30.9 percent, nearly doubling the initial figure.[2]

Another important observation is the upward trend in college costs. Over the past

[2]Source: U.S. Department of Commerce, Census Bureau, Current Population Survey (CPS), October Supplement, 1970 through 2020. See U.S. Department of Education, National Center for Education Statistics (NCES), Digest of Education Statistics 2021, table 302.60, (last accessed December 2023).

several decades, college tuition and fees have been increasing faster than the average prices in the economy. Figure 2 illustrates the average inflation-adjusted published tuition and fees (sticker prices) in various educational sectors over the past 30 years, specifically between 1991-1992 and 2021-2022.

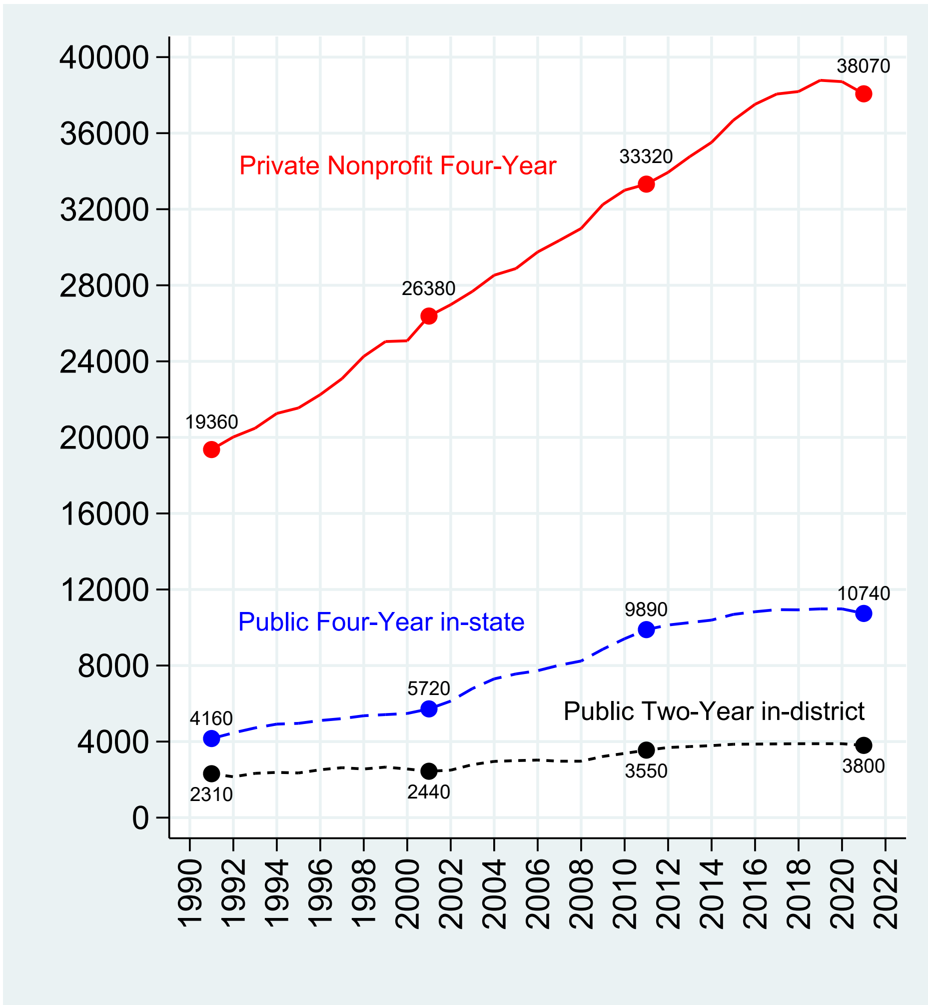

Figure 2: Inflation-adjusted average published tuition and fees in 2021 dollars by sector, 1991-1992 to 2021-2022
Source: College Board (2021), Trends in College Pricing and Student Aid 2021

Data reveals significant increases in college tuition and fees over the past decades. Figure 2 presents compelling evidence, indicating that between 1991-92 and 2021-22, the average tuition and fees experienced a substantial surge. Specifically, public four-year institutions' average tuition and fees rose from \$4,160 to \$10,740. Also, at private nonprofit four-year institutions, the figures increased from \$19,360 to \$38,070 (all values are in constant 2021 dollars). This data highlights the significant financial burden placed on students and families seeking higher education during this period.

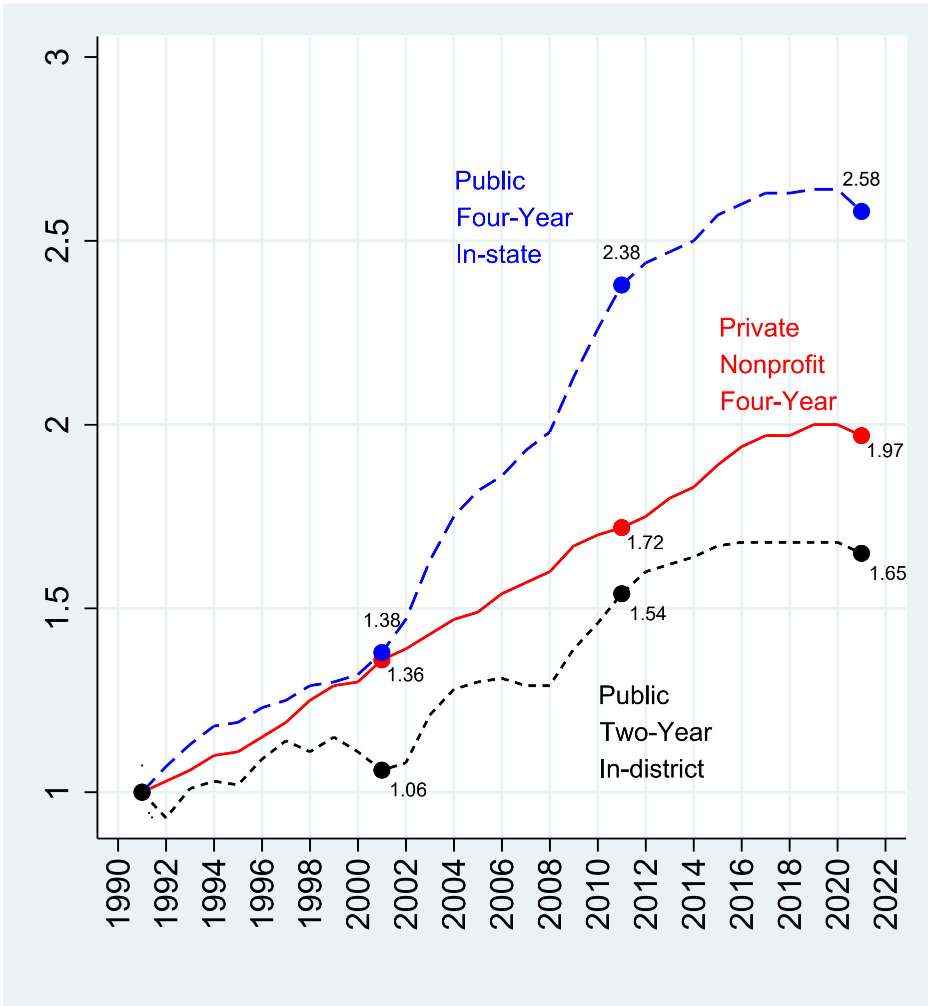

Figure 3: The growth of inflation-adjusted published tuition and fees relative to 1991-92
Source: College Board (2021), Trends in College Pricing and Student Aid 2021

As depicted in Figure 3, the upward trajectory of tuition and fees is particularly noticeable in public four-year colleges compared to other institutions. In the academic year 2021-22, the average tuition and fees for public and private four-year colleges were 2.58 and 1.97 times higher, respectively, than in 1991-92. This substantial cost increase, especially in public four-year schools, can potentially hinder the enrollment of young individuals from lower-income families who predominantly rely on public institutions rather than private ones. The disproportionate rise in tuition and fees at public colleges may challenge access to higher education, particularly for those with limited financial resources.

However, several financial programs in the form of loans and grants in the United States aim to make college education more affordable. These programs play a crucial role in supporting students financially. Figure 4 provides an overview of the primary sources of financial aid for U.S. undergraduate students, which comprise approximately 80 percent of the total financial aid available. These programs and grants help alleviate the financial burden on students and enable them to pursue higher education by providing crucial financial support.[3]

Two Federal programs significantly provide most Federal aid to college students: the Pell Grant and the Stafford Loan. The Federal Pell Grant is a need-based program primarily awarded to undergraduate students with exceptional financial needs. The Free Application for Federal Student Aid (FAFSA) process determines student eligibility for this grant. In the 2020-21 academic year, the Pell Grant and Federal Loan Programs collectively disbursed substantial financial support to undergraduate students, with $26 billion allocated for Pell Grants and $45 billion provided through Federal Loan Programs.

Figure 4 also shows that institutional grants in need-based, merit-based, or tuition discounts have experienced significant growth over the past decades. Institutional grants have been increasing rapidly to offset rising tuition and fees. In the academic year 2020-21, the deductions in college costs through institutional grants were more than three times higher than in 2000-01. This trend highlights the efforts made by colleges and universities to provide financial assistance to students and address the increasing financial burden associated with higher education. Figure 5 represents the financial assistance students receive through grants, which helps offset the cost of attending these institutions. More specifically, this figure illustrates how the average grant aid reduces the published price of college tuition and fees for first-time, full-time undergraduate students enrolled in private nonprofit four-year

[3]The remaining financial aid comes from Federal Veterans' benefits, private and employer grants, Federal education tax benefits, Federal Work-Study (FWS) funds, and Federal Supplemental Educational Opportunity Grant (FSEOG).

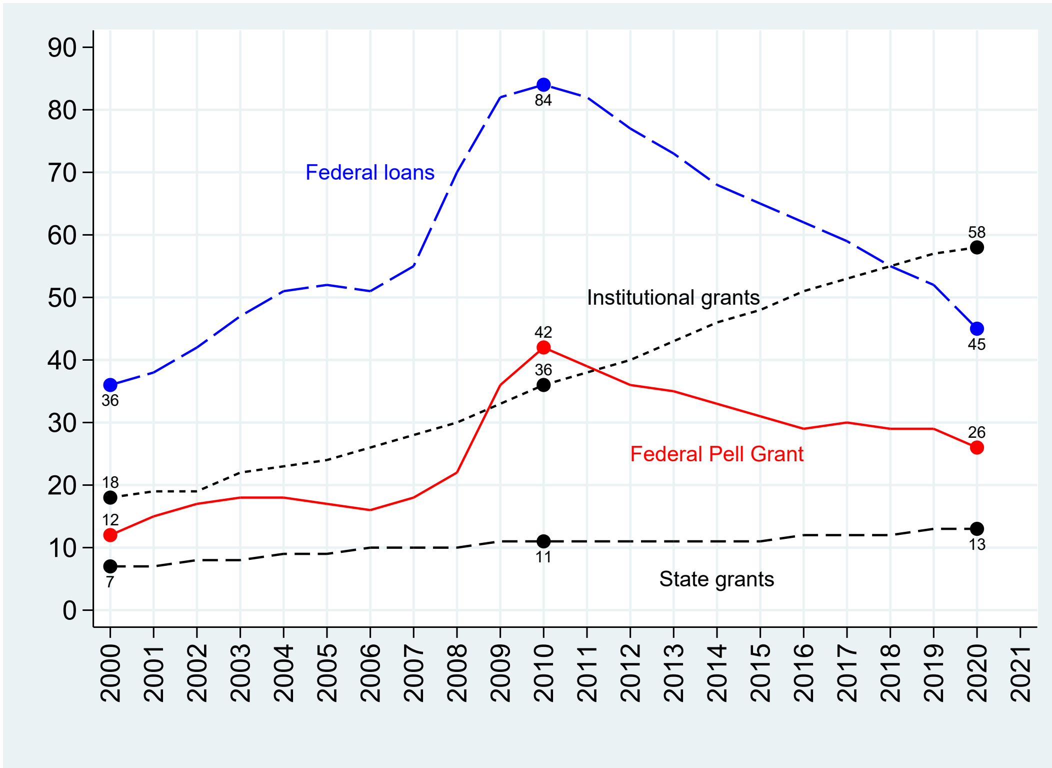

Figure 4: Main undergraduate student aid in 2020 dollars (in Billions), 2000-01 to 2020-21
Source: College Board (2021), Trends in College Pricing and Student Aid 2021

institutions from 2006-07 to 2021-22. Similarly, Figure 6 demonstrates the impact of average grant aid in reducing the published price of tuition and fees for students enrolled in public in-state four-year institutions. These figures highlight the importance of grant aid in making college education more affordable and accessible for students, as it helps offset the overall cost of tuition and fees.[4]

There is a widespread consensus that having an educated populace is crucial for the progress and well-being of society. The decision to attend university is life-changing and has significant implications across various aspects of individuals' lives. On average, individuals with higher levels of education tend to have better employment prospects and earning

[4]Notes from the College Board as the source of the figures: 1) Average net prices are calculated as the difference between published prices from the College Board's Annual Survey of Colleges and grant aid from IPEDS Student Financial Aid data. Because the latest year for which grant aid data are available is 2019-20, grant aid and net prices for 2020-21 and 2021-22 are projected by assuming per-student grant aid amounts are the same as in 2019-20 in constant dollars. 2) In 2019-20, 86% of the total \$23,080 and 49% of the complete \$8,100 in grant aid per student came from institutional grant aid provided by colleges and universities in the form of discounts from their published prices.

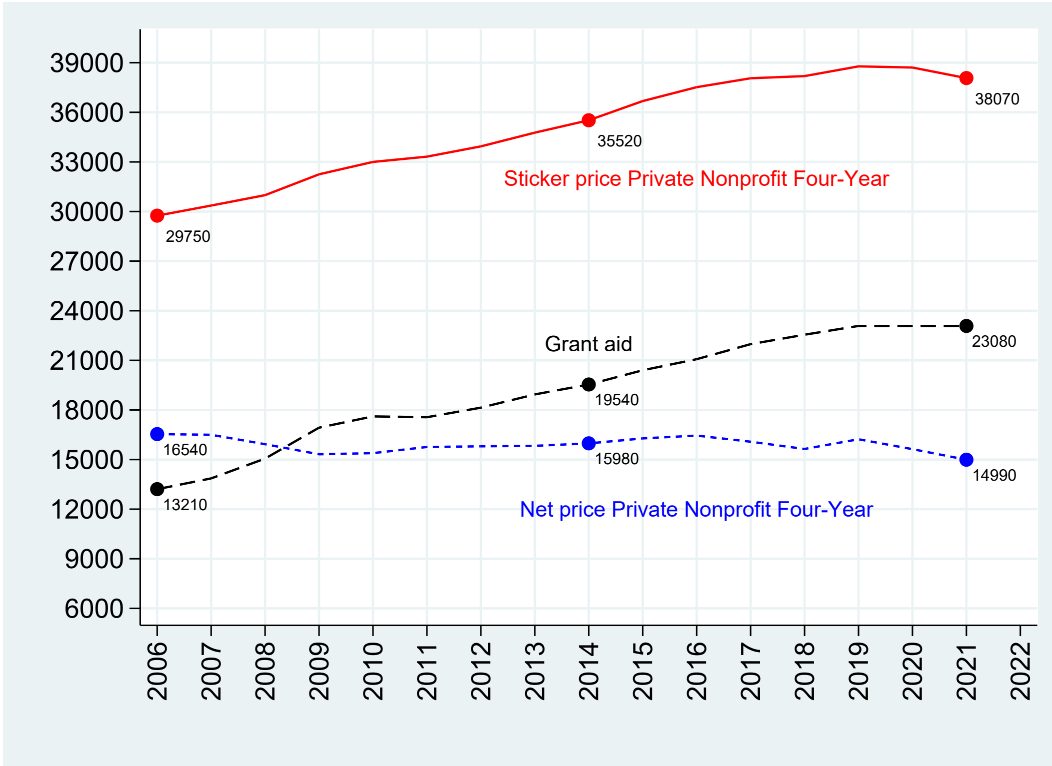

Figure 5: Average published and net prices in 2021 dollars, first-time full-time undergraduate students at private nonprofit four-year institutions, 2006-07 to 2021-22
Source: College Board (2021), Trends in College Pricing and Student Aid 2021

potential than those with lower education levels. Higher education equips individuals with the knowledge, skills, and qualifications employers value in today's competitive job market.

Academic literature has extensively studied the average return to postsecondary education and the college wage premium. Researchers such as Murphy and Welch (1992) have analyzed data from the Current Population Survey (CPS) to examine the college wage premium. Their study focused on full-time, full-year white male workers and observed the period between 1963 and 1989. Their findings indicated that, on average, college graduates earned 44 percent more per hour than high school graduates during this period. Similarly, Castro and Coen-Pirani (2016) utilized CPS data for white males who were full-time, full-year workers between the ages of 23 and 65. Their study focused on 2010 and showed that individuals with a four-year college degree earned approximately 60 percent more than high school graduates. Valletta (2016) researched March CPS data from 1979 to 2014. Their study focused on the average college wage premium over this period and found that it

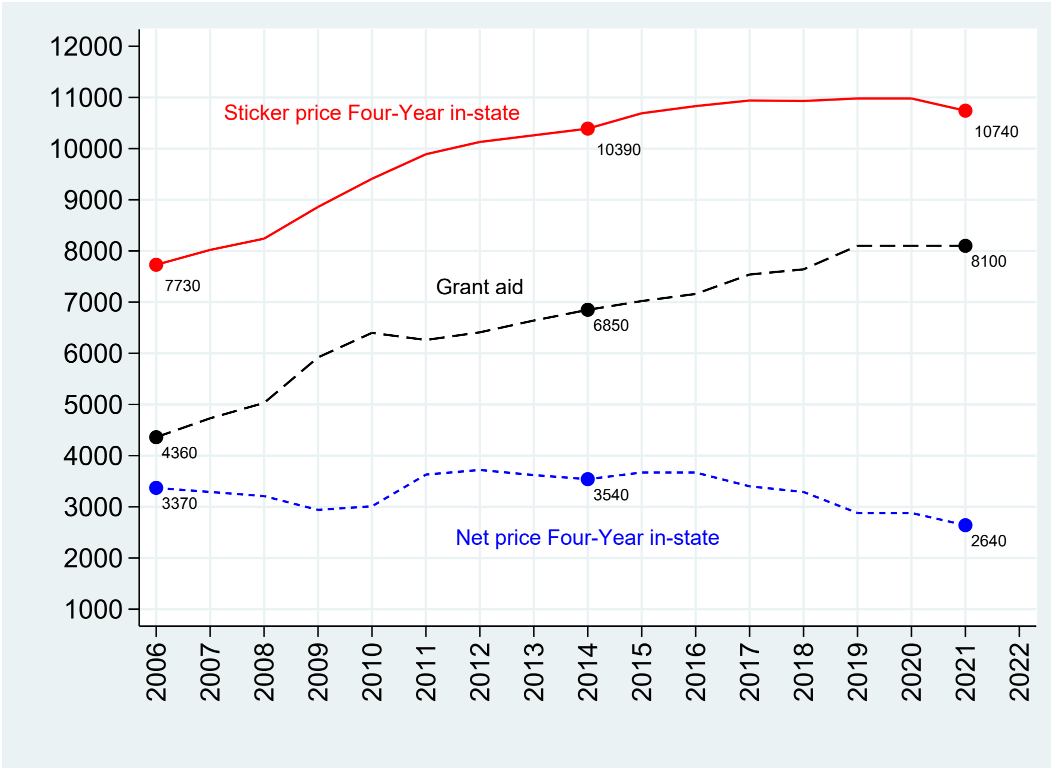

Figure 6: Average published and net prices in 2021 dollars, first-time full-time in-state undergraduate students at public four-year institutions, 2006-07 to 2021-22
Source: College Board (2021), Trends in College Pricing and Student Aid 2021

reached around 50 percent. This study suggests that, on average, individuals with a college education earned approximately 50 percent more than their counterparts with a high school education. (for surveys on the estimation of returns to schooling, see Belzil, 2007; Card, 1999, 2001; Meghir & Rivkin, 2011; Psacharopoulos & Patrinos, 2018).

There is a vast amount of literature highlighting a negative relationship between education and crime.[5] The relationship between education and crime has been extensively studied, with a substantial body of literature highlighting a negative correlation between the two. For example, Groot and van den Brink (2010) use data from "The Netherlands Survey on Criminality and Law Enforcement" conducted in 1996 to investigate the frequency of committing various crimes among respondents. The study's findings indicate that individuals with lower levels of education tend to commit more severe crimes than those with higher

[5] See among others Atems and Blankenau (2021), Bennett (2018), Fella and Gallipoli (2014), Groot and van den Brink (2010), Lochner (2004), Lochner and Moretti (2004)

education levels. For instance, the study reveals that individuals with lower vocational, secondary, and primary school education have a significantly higher frequency of threatening someone at least once, ranging from three to five times more than individuals with university degrees. These findings suggest that education plays a crucial role in reducing criminal behaviour. Higher levels of education provide individuals with increased opportunities for personal and socio-economic development, enhancing their social integration and reducing the likelihood of engaging in illegal activities.[6]

Another study by Lochner and Moretti (2004) use various data sources to examine the relationship between education and participation in illegal activity. They use data on incarceration from the Census of Population and FBI Uniform Crime Reports and self-report data on criminal activity from the National Longitudinal Survey of Youth (NLSY). The study's findings suggest a negative relationship between education and criminal behaviour. Specifically, the estimates indicate that an additional year of schooling significantly reduces the probability of incarceration. For individuals of white ethnicity, another year of education is associated with a 0.1 percentage point decrease in the likelihood of imprisonment. However, for Black individuals, the effect is even more pronounced, with estimates ranging from a 0.3 to 0.5 percentage point reduction in the probability of incarceration.

Indeed, attending university or obtaining higher levels of education can positively impact health outcomes and health-related behaviours. Research has consistently shown that individuals with higher education tend to experience better overall health, adopt healthier lifestyles, and engage in preventive health practices. Grossman (2006) provides theoretical foundations for understanding the potential role of educational investments in health. He raises questions regarding the relationship between education and health, such as whether more educated individuals are generally healthier, less likely to smoke cigarettes, more likely to have healthier and better-educated children, and whether their consumption patterns differ from those with lower levels of education. Furthermore, Grossman presents extensive empirical evidence that supports a positive correlation between education and healthy behaviours. This evidence suggests that higher levels of education are associated with a

[6] Other severe crimes include assaulting people and inflicting injury by a weapon.

greater likelihood of engaging in health-promoting behaviours and making informed health-related decisions.[7]

This dissertation seeks to contribute value to the existing literature on higher education financing by investigating the relationship between college costs and schooling decisions. The primary focus is to understand how different financial aid policies influence the choices of high school graduates when pursuing higher education. The study aims to address several fundamental questions related to education, including the characteristics of those who attend college the most. Furthermore, the research aims to analyze the varying effects of distinct financial aid policies on college enrollment decisions, particularly in identifying the most cost-efficient approach.

Additionally, this study delves into the decision-making process regarding college majors, explicitly focusing on the distinction between STEM and ARTS fields.[8] The research investigates whether educational policies that attract more high school graduates to college also influence their choice of major, specifically analyzing whether these students opt for STEM or ARTS disciplines. I have chosen STEM and ARTS to represent two distinct majors with totally different returns on schooling and wage premiums.

Contribution to the literature

My study is based on Ionescu (2009). However, my model introduces several crucial distinctions from the existing literature. First, within a computational framework, it incorporates two distinct fields of study, STEM and ARTS. To my knowledge, this is the first paper to attempt to model these two fields of study using a life cycle model and panel data. Identifying the fields of study is a big challenge in the existing datasets.[9] This setup allows for a more detailed examination of the effects of various educational policies on college

[7]See Kemptner, Jürges, and Reinhold (2011), James (2015), and Heckman, Humphries, and Veramendi (2018) as examples of more recent studies.

[8]STEM stands for science, technology, engineering, and mathematics. I created STEM occupations using the Standard Occupational Classification (SOC) 2010. ARTS refers to specific Non-STEM occupations such as Arts, Design, Entertainment, and Media Occupations, Community and Social Service Occupations, and Library Occupations, in Chapter 2, I will explain more about categorizing the college majors used in this dissertation.

[9]I will explain this issue more in Chapter 2.

enrollment and its composition.

Second, the objective function in my model considers not only the utility derived from consumption but also the disutility associated with investing in human capital and participating in the labour market. This dual-component objective function provides a more comprehensive representation of individuals' decision-making process, as it accounts for the trade-offs between investing in education and working to earn income. Third, the financial aid system in my model combines need-based and merit-based components with precise functional forms clearly defined, providing a more realistic representation of the financial assistance students might receive based on their initial asset and ability levels.

Lastly, I improved the base model features to make it more practical. I defined proxies for accumulating credits required to graduate: a minimum college study time (25%) and a minimum increase in human capital during college as a proxy for passing the necessary credits. The second part defines percentage growth thresholds in the initial human capital during college (20% for STEM and 10% for ARTS). These conditions relate graduation to "learning ability" and the required effort (time to study) to graduate. I will explain all model features throughout the paper.

My dissertation proceeds in the following way. Chapter 1 provides an extensive literature review of educational choices. Chapter 2 explains the empirical work using the PSID dataset. This chapter derives the earnings statistics necessary to match the model to the data. Also, in this chapter, I create the age profiles of agents and derive the relevant parameters. Chapter 3 describes the model, results, and policy experiments. In the end, the Summary part summarizes and concludes.

Chapter 1

Educational Choice Literature

1.1 Introduction

The main focus of this literature review is on the determinants of choosing a college and, more specifically, college majors. There is a broad literature using empirical Microeconomics and Macroeconomics techniques which I try to categorize and discuss the central studies in general and some of them in detail.

Since studying at school is a form of investment in human capital, this chapter starts with a brief explanation of the *Human Capital Theory* presented in section 1.2. Then, in section 1.3, I investigate the reduced-form models that show the correlation between human capital formation and wages. Various human capital studies extensively use wages as the most explicit outcome of this investment that could be measured and found in the data. This section discusses the seminal papers of Mincer (1958, 1974). Section 1.4 introduces the pioneers of structural models. The first two papers contain theoretical models (Ben-Porath, 1967; Roy, 1951). In these models, individuals choose their level of schooling. Therefore, investing in human capital is treated as endogenous. The authors model schooling decisions jointly with wage outcomes such that the causal effect of education is identifiable separately from the spurious effects. The following two studies are the pioneers of static and dynamic empirical Roy's self-selection model (Keane & Wolpin, 1997; Willis & Rosen, 1979).

Section 1.5 discusses the sequential learning models in which agents update their expectations about their endowments (ability and preferences) and their labour market outcomes. Next, in section 1.6, I will explain the new trend in schooling literature in which researchers rely on datasets derived by eliciting individuals' beliefs and expectations categorized as subjective expectation literature.

Section 1.7 presents a historical view of schooling in the United States. I will discuss three papers explaining fascinating aspects of historical trends in the U.S. labour market starting from the twentieth century (Castro & Coen-Pirani, 2016; Hendricks, Herrington, & Schoellman, 2021; Hendricks & Schoellman, 2014). At the end of this chapter, section 1.8 discusses various determinants of college or college major choices, such as lifetime earning expectations, non-monetary factors (tastes for schooling and learning ability), and parental transfers.

1.2 Human capital theory

In a broad definition, human capital is viewed as any stock of knowledge/skills or characteristics that contributes to an individual's "productivity." The sources of human capital could be either the innate ability or accumulation by schooling or other types of informal training, such as those workers acquire after schooling.[1,2] The Human Capital Theory gained prominence notably with the works of Mincer (1958, 1974), Schultz (1960, 1961), Becker (1962, 1964), and Ben-Porath (1967). This theory attempts to explain the

[1](Ben-Porath, 1967, p.359) defines human capital accumulation technology as "a complicated system of technical and institutional relationships covering a wide spectrum of activities including formal education, acquisition of skills on the job, child care, nutrition, health, etc."

[2]Heckman, Lochner, and Taber (1998) He refers to schooling as extensive margin and on-the-job training as intensive margin. The training provided at school is also called formal education, education, or schooling. The training delivered out of school is known as informal education, informal training, on-the-job training, or post-schooling training.

structure and distribution of earnings by investing in human capital.[3]

Education and training are the most critical inputs in human capital. In a seminal paper, Schultz (1960), one of the founders of the Chicago School of Human Capital Analysis first identifies "human capital" narrowly with investment in education. He puts forward the proposition "to treat education as an investment in man and to treat its consequences as a form of capital. Since education becomes a part of the person receiving it, I shall refer to it as human capital" (p.571). He discussed the role of human capital in accounting for the "unexplained" portion of increases in national income after accounting for the growth of inputs such as physical capital and the amount of labour that is not productivity adjusted.[4] He argues that investment in formal education could largely account for the increase in per capita income in the United States. Further college education significantly impacts skills if it builds on a solid fundamental skill foundation such as higher innate ability or higher level of human capital accumulated. In other words, skill formation over the life cycle strongly depends on the level of skills accumulated at the early life cycle stage: "skill begets skill through a multiplier process" (Cunha, Heckman, & Lochner, 2006, p.698).

Furthermore, many scholars broadened the concept of human capital from formal schooling to include additional sources of human capital accumulation, such as on-the-job training. For example, Schultz (1961) mentions on-the-job training as another human capital investment category. Becker (1962, 1964) categorizes college education and on-the-job training as human capital investment activities influencing future real income. Becker (1964) defines human capital as "activities that influence future monetary and psychic income by increasing resources in people" (p.1), and its primary forms are schooling and on-the-job training.

[3]The human capital approach is considered by (Becker, 1964, Ch.3, p.66) as "the means of bringing the theory of personal income distribution back into economics."

[4]In the second footnote of the first page of the paper, the author states, "By "unexplained" I mean here the increases in measured national income that exceed the increases in measured resources, treated as inputs."

1.3 Reduced-form relationship between wages and schooling

1.3.1 Compensating differences model (Mincer 1958)

Mincer (1958)'s model is said to be a non-economic or accounting model. It uses compensating wage differential by equating the present value of lifetime earnings of two cases: without and with schooling, net of costs associated with education. The procedure is similar to equating the net present value of two projects, A and B, and finding the investment return.

The model environment is certain, and the credit markets are perfect. Individuals are *ex-ante* identical, have the same ability level and can benefit from investment in human capital with no difference in the environment, luck, and family wealth. There is no direct cost of schooling, such as tuition, fees, books, and rooms. The only cost of education is the foregone earnings. For each level of education, s, the annual income, y_s, remains constant over the life cycle.

The life span (T) is identical for all individuals. Occupations differ in the amount of education required. Therefore, people need a compensating wage differential to work in professions that require a more extended schooling period because the length of working life for educated people is less than that of non-educated individuals.

Consider two individuals, with and without schooling. Define V_0 as the present value of lifetime earnings for individuals without schooling and T years of working. Also, define V_s, the same for a person who plans to study s years of education and labour income stream starts afterwards. In a continuous framework, these discounted lifetime earnings could be shown as

$$V_0 = \int_0^T y_0 \; e^{-rt} dt,$$

$$V_s = \int_s^T y_s \; e^{-rt} dt.$$

Also, define the internal rate of return to schooling, r, as the discount rate that equates to the net lifetime earnings for all individuals. It is assumed to be the same for all individuals who either directly join the labour market without schooling or attend school with any length of education (s). Then, the internal rate of return for these two individuals' investment plans is such that the present value of lifetime income streams with and without schooling are equal,

$$V_s = V_0,$$

$$\int_s^T y_s \; e^{-rt} dt = \int_0^T y_0 \; e^{-rt} dt,$$

The goal is to find the relationship between y_s and y_0. Therefore, first, I take these constant values out of the integral

$$y_s \int_s^T \; e^{-rt} dt = y_0 \int_0^T \; e^{-rt} dt,$$

and then solve the definite integrals

$$\frac{y_s}{-r} \Big(e^{-rt} \Big) \Bigg|_s^T = \frac{y_0}{-r} \Big(e^{-rt} \Big) \Bigg|_0^T,$$

$$y_s \Big(e^{-rT} - e^{-rs} \Big) = y_0 \Big(e^{-rT} - 1 \Big).$$

The next step shows the simplification by multiplying and dividing the right-hand side by an identical value,

$$\frac{y_s}{y_0} = \frac{\Big(e^{-rT} - 1 \Big)}{\Big(e^{-rT} - e^{-rs} \Big)} \times \frac{-e^{rT}}{-e^{rT}}.$$

Define $p = y_s / y_0$, a representation of *schooling premium*, then

$$p = \frac{e^{rT} - 1}{e^{r(T-s)} - 1}. \tag{1}$$

Implications of the model

Equation (1) reveals that p is: (1) larger than unity for $s > 0$, (2) a positive function of s, (3) a positive function of r, and (4) a negative function of T.

The first result shows that educated people receive a higher annual income than individuals without schooling.[5] The second statement declares that higher education is associated with higher income stream levels after schooling. The third outcome mentions that the higher the rate at which future income is discounted, the more significant the difference between earnings because the sacrifice involved in the act of income postponement is more critical. The last result shows that the shorter the life span, the more the schooling premium is prominent because a relatively shorter period will remain to recoup the opportunity costs of schooling.

The model delivers exciting results. However, it is a preliminary model based on many simplifying assumptions. For example, the model assumes that the yearly income remains flat after schooling and is unaffected by years of experience. Therefore, the model cannot explain the concave shape of the age-earning profile.

1.3.2 Accounting-identity model (Mincer 1974)

The next Mincer's model (Mincer, 1974) relaxes some of the assumptions described in the previous section and introduces "*experience*" to the model.

The model delivers the famous *Mincer equation*. Mincer (1974) attempts to use human capital as the primary explanatory tool for empirical findings.[6] The author defines h_t as the potential human capital embedded in individual at time t:

$$h_t = h_{t-1} + rc_{t-1}, \tag{2}$$

[5] The author assumes the values of r and T to be in a neighbourhood of 0.04 and 50, respectively.

[6] Using human capital in Mincer's model has similarities and dissimilarities with Ben-Porath (1967). I will explain them at "interpretation of the Mincer wage equation using Ben-Porath model."

where c_{t-1} is the cost of accumulating human capital. In other words, c_{t-1} is the dollar amount of net investment in the period $t-1$.[7] The human capital is translated into dollar amounts representing the potential earnings of an individual. Therefore, h_{t-1} is the "gross" earnings, that is, earnings from which the investment expenditures are not deducted, and r is the rate of return on investment in human capital. By assumption, r as an average return to investment is exogenous and is the same in each period.

Investment in human capital is expressed as a ratio of investment expenditures over potential earnings, $k_t = c_t/h_t$. This ratio is viewed as a time-equivalent amount of investment in human capital. The main reason for this assumption is the lack of data on individual monetary instalments of investment in human capital accumulation. However, data on time allocated for this investment are more observable. For example, when individuals attend school, it is assumed that they are entirely devoting their time to study; therefore, during schooling periods, $k_t = 1$. But while working, they allocate a positive fraction of their time to accumulate human capital

$$k_t = \frac{c_t}{h_t} = \begin{cases} 1 & \text{during schooling,} \\ < 1 & \text{after schooling.} \end{cases} \tag{3}$$

Appendix B.1 starts from Equation (2) and explains the steps to find the *the popular Mincer wage equation*:

$$\ln y = \beta_0 + \beta_1 s + \beta_2 x - \beta_3 x^2 + \varepsilon. \tag{4}$$

Equation (4) is y is a measure of income or wage rates as a function of completed years of schooling (s) and the number of years an individual has worked since schooling (x).

The key assumption of Mincer (1974) is the exogenous investment rule in human capital, $k_t = \kappa(1 - \frac{x}{n})$, expressed as Equation (54) in Appendix B.1. By introducing this equation, Mincer (1974) assumes that individuals invest in human capital when working after leaving school, and the rate of post-school investment linearly decreases when approaching the end

[7]Cost of accumulating human capital could be tuition and cost-of-living differential attributable to schooling minus student aids, grants and scholarships.

of the working life cycle. This specific contribution of the "experience" factor (x) into the regression model delivers a concave shape of individuals' life cycle earnings profiles, an improvement compared to the previous compensating difference model of Mincer (1958).

While the Mincer equation has been recognized for its theoretical foundation and empirical results in labour market economics, Equation (4) is not without faults and has faced many critiques from various perspectives.

Critiques to the Mincer model

The regression model creates a statistical bias called "*ability bias*," an object of much debate over the past decades (see, for example, Belzil, 2007; Belzil & Hansen, 2002, 2007; Card, 1999; Griliches, 1977; Hermann, Horvath, & Lindner, 2022). The problem occurs by measuring the causal effect of schooling on wages by OLS regression when there is no measure of "learning ability" in the model. Where the ability is a left-out variable hidden in the error term, ε, correlated with the level of schooling, $cov(s_i, \varepsilon_i) > 0$, it happens because "conventional wisdom" says that individuals with higher levels of learning ability and education (with higher s_i) are also more able in the labour market and earn more (with higher ε_i). The higher ability helps students accumulate human capital and increase their working ability over time. Therefore, β_1 or the return on schooling partially captures the effect of learning ability on earnings, hidden in the residual, ε_i. As a result, the regression delivers higher β_1 than expected. In other words, this problem of endogeneity results in the "upward bias" of the rate of return on schooling, β_1. This overestimation of the true causal effect of schooling on wages is called "positive ability bias".[8]

The empirical evidence strongly rejects Mincer's implicit assumption that internal rates of return to each year of schooling, β_1, are identical to all levels of education and for various cohorts over time. Heckman, Lochner, and Todd (2003) criticize Mincer's model because it treats the relationship between years of education and wages as linear. Also, Heckman,

[8] Griliches (1977) points out the possible negative "ability bias" as well because individuals who have the higher (earning) ability also have a higher opportunity cost of attending school, and their return on schooling would be lower than expected. Put differently, their ability, hidden in the error term, negatively correlates with the level of schooling. It seems that high-earning athletes with low educational attainments are relevant examples of these individuals.

Lochner, and Todd (2008) have tested and rejected the linearity with US census data (1940-2000).

The Mincer equation does not consider the educational credentials' direct impacts on earnings, called "credential" or "sheepskin" effects.[9] The return to a year of education should be higher between 15 and 16 years (college credential effect) than for other years of schooling. Card and Krueger (1992) estimate return to education relationships for three cohorts of white men born in Alabama or Georgia (1920-29, 1930-39, and 1940-49) and three cohorts of white men born in California. They show that log earnings between 15 and 16 years of schooling are higher than those of other schooling levels, consistent with the credential effects. Also, they find that the earnings-education relations are not the same for different cohorts.

Heckman et al. (2006) show that while many of Mincer's assumptions hold in the 1960 data for the U.S. labour market that Mincer analyzed, they are not valid in later periods. For example, one drawback of Mincer's model is the assumption that individuals earn nothing while in school. In reality, over half of the current undergraduates work for pay while college enrollment.[10]

However, serving as the point of departure for most empirical studies, Mincer's accounting-identity model greatly influenced how economists estimate education profitability. This model has been estimated on thousands of datasets for many countries and time periods, which makes it one of the most widely used models in empirical economics.[11]

[9] Heckman, Lochner, and Todd (2006) use the term "sheepskin effects" to refer to nonlinearities or vast rates of return at degree-granting years of schooling.

[10] Source: Learning While Earning: The New Normal, and Improving Educational Opportunities for Students Who Work , (last accessed December 2023).

[11] See, e.g. Psacharopoulos (1981), Psacharopoulos and Patrinos (2004, 2018), Montenegro and Patrinos (2014), and Patrinos (2016) for surveys of an abundant Mincer-based earnings literature. For example, Psacharopoulos and Patrinos (2018) collect 1,120 estimates for 139 countries over 65 years, most of them based on the Mincerian earnings function.

1.4 Pioneers of structural models

It is already discussed that the OLS regression technique suffers from *ability bias* and delivers an overestimate of the true return to schooling. One way to deal with the problem of ability bias is to augment OLS wage regression with a measure of ability, such as the Armed Forces Qualifications Test (AFQT), which measures basic quantitative and analytical skills. Another approach is to use fixed effects (within estimators) by using data on monozygotic twins - who are genetically identical but may differ in birth weight.

One more approach is to use instrumental variables (IVs). These regression models rely on an exogenous observable measure of the labour market ability variables correlated with schooling but uncorrelated with the error term of the wage equation. However, Heckman et al. (2006) state that traditional instruments used in the instrumental variable estimation are not strong, and the empirical estimates of the return to schooling are not decisive.

Moving forward from reduced-form to structural models, in this section, first, I introduce the seminal work of Ben-Porath (1967), who extends the optimal human capital investment decision from a one-time decision framework to a life cycle setting. Decomposing wage into skill price and quantity, the Ben-Porath model attempts to elaborate the optimal investment path in human capital over the life cycle.

1.4.1 Ben-Porath dynamic model of human capital accumulation

This section presents Ben-Porath (1967) as the first scholar who formalizes the accumulation of skills (human capital) within an explicit optimization framework and investigates wage growth over the life cycle. The main question in the model is: What is the optimal path of investment in human capital?

Ben-Porath's model delivers fantastic results. Individuals optimally invest in human capital production early in life when they have a relatively lower stock of human capital.

Also, the model, endogenously, can generate a hump-shaped life cycle profile for accumulated human capital and wages. Furthermore, the growth of human capital and wages is higher for higher-ability people because, in the Ben-Porath model, human capital production is a positive function of learning ability. As a result, inequality among educational groups over the life cycle is highly affected by their initial level of learning ability.

Ben-Porath's original model is in continuous time and assumes a finite time horizon. The following ordinary differential equation characterizes the dynamics of the system

$$\dot{h}(t) = \overbrace{f\Big(s(t), h(t), d(t)\Big)}^{q(t)} - \delta h(t), \tag{5}$$

Equation (5) presents a technology by which an individual can accumulate a homogeneous human capital, $h(t)$.[12] The rate of change in human capital stock at time t, $\dot{h}(t)$, contains two parts: the gross addition to the human capital,

$$q(t) = a\Big(s(t)h(t)\Big)^{\alpha} d(t)^{\beta}, \tag{6}$$

and the depreciation of human capital at time t, $\delta h(t)$. Where $a > 0$ is the measure of the individual's ability to produce human capital, assumed constant over the life cycle. $h(t)$ is the stock of human capital by date t, and $s(t)$ denotes the time allocated to invest in human capital formation,

$$0 \leq s(t) \leq 1, \tag{7}$$

$s(t) = 1$ could be interpreted as full-time schooling, and $s(t) < 1$ as the on-the-job training, devoting some of the unit time endowment to learning rather than production. d_t is the quantity of "purchased inputs", the price of which is denoted by p_d. The curvature parameters of the production function $\alpha, \beta > 0$, where $\alpha + \beta < 1$. Individuals accumulate human capital endogenously but lose it exogenously at depreciation rate $\delta \in [0, 1)$.

There is a competitive market for human capital, and each individual is assumed to

[12] Homogeneous human capital (or single-skill) is when all units of human capital are perfect substitutes for each other in earning production and therefore add the same amount to earnings (Becker, 1967).

possess only a tiny fraction of the total stock of human capital. Therefore, individuals face a given rental rate of human capital, w, independent of the volume of services they offer by their implied quantity of human capital, $h(t)$. Thus the earnings capacity at time t equals the market value of the full services of human capital the individual can offer

$$Y(t) = wh(t).$$

But the disposable income, $y(t)$, is the earnings capacity net of investment costs,

$$y(t) = wh(t) - c(t). \tag{8}$$

Neither w nor $h(t)$ are observable, but the earnings, $y(t)$ are observable. $c(t)$ represents the investment costs of producing human capital; it also has two components

$$c(t) = ws(t)h(t) + p_d d(t). \tag{9}$$

The first part of the investment costs represents the value of the productive services withdrawn from the market, $ws(t)h(t)$. The second component shows the value of purchasing other inputs or the direct cost of accumulating human capital, $p_d d(t)$.[13]

Schooling is viewed as a period of full-time investment, $s(t) = 1$, resulting in zero earnings during study at school. However, during working periods, the "on-the-job training" (OJT) is considered as a time of partial investment, $s(t) < 1$, with an indirect cost of investment in human capital equal to $ws(t)h(t)$ as the "foregone earnings" or the opportunity cost of producing an extra quantity of human capital. In other words, workers do not receive a wage for a fraction of the time they invest in human capital accumulation.

Ben-Porath assumes $s(t)$ as the proportion of time devoted to the production of human capital if "individual's activities are not "mixed", that is if there is no joint production of earnings and human capital" (p.354). In other words, the individual's activity does

[13] Examples of the monetary value of purchased inputs, $p_d d(t)$, could be school tuition and fees, the cost of buying a trainer service or buying a new computer.

not include "learning by doing" (*LBD*), in which human capital is accumulated through experience or skills and output is jointly produced during the working hours (Wolpin, 2003). As explained in Imai and Keane (2004), in *LBD*, human capital evolves as a function of the current labour supply. Hours of work today increase the accumulated human capital and wage tomorrow. Individuals may recognize that working today provides labour income today and increases the wage in the future as they become more productive at the job the more they work.[14]

Obtaining optimal human capital investments requires equating both the marginal benefit and the marginal cost of producing human capital. Finding these values needs to solve the agent's problem. Given initial human capital, h_0, individuals maximize the present value of their disposable income over the life cycle ending at time T, which is assumed to be the end of their life,

$$\int_0^T e^{-rt}\Big\{wh(t) - c(t)\Big\}dt = \int_0^T e^{-rt}\Big\{wh(t)\Big(1 - s(t)\Big) - p_d d(t)\Big\}dt, \tag{10}$$

subject to Equations (5) to (7).

Ben-Porath assumes a complete market where individuals can borrow and lend at a constant interest rate (r). Also, he assumes that individual utility is not a function of activities involving time as an input. In other words, leisure is not valued in the model setup. Also, there is no uncertainty in the model.

To reach the results of Ben-Porath's model, one needs to put more effort into the details of the model. The problem mentioned in Equation (10) can be solved by setting up the present value Hamiltonian, as described in Appendix B.2. This appendix explains the steps to find the optimal level of human capital produced at time t, shown in Equation (11),

$$q(t) = a\Big(\frac{a\alpha}{r+\delta}\Big)^{(\alpha+\beta)/(1-\alpha-\beta)}\Big(\frac{\beta w}{\alpha p_d}\Big)^{\beta/(1-\alpha-\beta)}\Big[1 - e^{-(r+\delta)(T-t)}\Big]^{(\alpha+\beta)/(1-\alpha-\beta)}. \tag{11}$$

[14] Taber and Vejlin (2020) is a more recent work that uses *LBD* notion of human capital accumulation along with other key components of the Roy model, compensating differentials, and a search model.

Some results of Ben-Porath model

Taking the derivative of Equation (11) with respect to time shows that the production of human capital decreases $\left(\partial q(t)/\partial t < 0\right)$ over the life cycle, and it will be zero at $t = T$. This result coincides with the decreasing trend of the marginal benefit of acquiring one more unit of human capital over the life cycle.

Therefore, individuals would optimally specialize in human capital production early in the life cycle when an individual's stock of human capital is relatively lower than the rest of the life cycle. Thus, schooling as a "full-time investment" would come first in the life cycle.

This feature, along with an assumption of a positive depreciation rate of human capital, the model can generate a hump-shaped life cycle profile for the human capital. Similarly, wage follows the same pattern because it multiplies skill price and stock of human capital.

Also, Equation (11) reveals that the production of human capital, $q(t)$ is a positive function of ability, a. The growth of human capital and wages is higher for higher-ability people. Therefore, heterogeneity in the initial ability increases earnings inequality among different ability groups over the life cycle.

Interpretation of Mincer wage equation using the Ben-Porath model

Mincer (1974) and Ben-Porath (1967) models are similar in that both use and start from human capital as the primary explanatory tool to explain the life cycle earning profiles. However, there is a fundamental difference between these two models. Mincer dictates an exogenous rule for investment in human capital, Equations (47) and (54). While in Ben-Porath, investment decisions are taken endogenously based on the maximization of lifetime disposable income, Equations (78) and (80).

One may be interested in viewing schooling and on-the-job training in the Mincer model from another aspect and represent the Mincer wage equation by defining a specific production function for human capital, different from the Ben-Porath human capital function. This representation is done first by taking the log of both sides of the wage equation of the

Ben-Porath's model ($y_t = wh_t$),

$$\ln y_t = \ln w + \ln h_t, \tag{12}$$

where y_t is the wage (or the potential earning when an individual works full time), w is the rental rate of human capital, and h_t is the stock of human capital at time t. Then define the following as the implicit production function for the human capital used in the Mincer's model

$$h_t = h_0 \exp(\beta_1 s + \beta_2 x - \beta_3 x^2 + \varepsilon), \tag{13}$$

where s is the years of schooling, x is the after-school work experience, and h_0 is the measure of the dispersion of initial human capital or skills among individuals at the beginning of schooling. These initial market-valued skills are accumulated before schooling with the help of parents or society. Taking log of equation (13) and substituting it into equation (12) results in

$$\ln y = \underbrace{\ln w + \ln h_0}_{\beta_0} + \beta_1 s + \beta_2 x - \beta_3 x^2 + \varepsilon. \tag{14}$$

Equation (14) is similar to Equation (4), the Mincer wage equation, where the intercept (β_0) contains two terms: the rental rate of human capital or the skill price and the level of the initial level of skill of individuals ($\ln w + \ln h_0$). However, this interpretation has its drawbacks.

The regression model results in a unique intercept parameter β_0. But people are different in the initial human capital or skills ($\ln h_0$) and may enjoy different skill prices ($\ln w$). The regression model can not show this important feature. Also, people are heterogeneous in their ability level and may have different values of return on education and experiences. But the model delivers unique values of β_1, β_2, and β_3 for all individuals.

There is another problem with the new representation of the Mincer wage equation. Imagine that there are two cohorts. It is not possible to infer changes in wage dispersion by claiming that the return to human capital (skill) is changed over time for two cohorts because the intercept (β_0) contains two items and not just the skill price ($\ln w$). Therefore, with the new interpretation, one can not identify the changes to return to skill.

The Ben-Porath's model evolved to understand individuals' decisions for investing in human capital and the implications for lifetime earnings of this investment. However, it uses one type of human capital or skill in the model. In the following sections, I explain more about models in which the skills are multi-dimensional.

1.4.2 Roy's self-selection model

Roy (1951) develops a seminal occupational choice model and analyzes the impact of self-selection in occupational choice, where agents choose the sector that provides them with the higher wage. As a pioneer work in self-selection literature, Roy's model introduces the notion of *"comparative advantage"* in individuals' selection process. Related to the topic of this thesis and in the framework of Roy's model, one may ask why individuals choose a college, specifically STEM or ARTS. Why do some students join the labour market after high school? What are their "comparative advantages" and how do they affect the agents' decisions? These are part of questions that Chapter 3 of this dissertation tries to answer them using an appropriate model calibrated to the existing U.S. data.

The Roy model fits in the framework of a multi-skill model. This framework assumes that each individual has both occupation-specific skills required by jobs. However, skills are treated as initial endowments, and individuals make no human capital investment (or skill acquisition) decisions. Given the text's verbal (no mathematical notation) style, going through the model's key characteristics is somewhat challenging.

The main message of Roy is that switching from one occupation to another depends not only on the mean earnings but also on the distribution of income that arises from economic processes and the correlation between skills used among professions. Roy's original model is based on two occupations – (rabbit) hunting and fishing. Workers have skills in both professions, but each skill only applies to the relevant sector. Individuals can not use both skills simultaneously; hence, they self-select the occupation that gives them the highest expected earnings. The main goal is to understand self-selection: Will the individuals with the highest fishing (hunting) skill levels choose to fish (hunt)? In other words, do the best fishermen fish? And do the best hunters hunt?

It is crucial to notice that data provides the information of just one job at a time for each individual or the "factual" job. The jobs that are not realized are called counterfactual because their wage outcomes are not measured in the data. For example, people chosen to be hunters can see their earnings just as hunters, not fishermen. This invisibility of earning outcomes of counterfactual choices is a big challenge in the model.

Positive selection into fishing and hunting occupations

As explained in Appendix B.3, if $\sigma_{11} > \sigma_{12}$, then the positive selection into fishing happens - the best fishers fish, where σ_{11} is the variance or the dispersion of fishing skill and σ_{12} is the covariance between fishing and hunting skills. Similarly, by repeating the same operations for the hunting skill, it could be shown that if $\sigma_{22} > \sigma_{12}$, then the positive selection into hunting occurs - the best hunters hunt.

Roy introduces two factors in determining the self-selection phenomenon: the correlations among skills in the population (σ_{12}) and the dispersion (or concentration) of the logarithms of individual output at each occupation (σ_{11} or σ_{22}). If the correlation between the skill types in the population is a negative or small positive number, then the "comparative advantage" matters, and positive selection for skills occurs. But if the correlation is high, the self-selection happens only for the occupation with high dispersion in society. Conversely, if the correlation among skills is very high, then the "absolute advantage" matters. Those who are the best in one job are also the best in another occupation, and no self-selection happens.

Roy assumes fishing occupation needs higher levels of ability than hunting rabbits. The author calls fishing and hunting "superior" and "inferior" skills because the distribution of fishing ability is assumed to be more dispersed, and hunting ability is more concentrated. Consequently, fishing is more prone to self-selection than hunting.

Applying Roy's model to educational choices, suppose two potential jobs are available for a representative individual in the economy: A white-collar job requiring a college degree and a blue-collar job requiring a high school diploma. The correlation between the two positions is low and sometimes even negative, meaning that those good at a white-collar job are not good at a blue-collar job and vice versa. Therefore, out of two potential occupations, individuals choose the one they perform better and receive higher earnings than if they had decided to work in another profession. In other words, they pick up (self-select) the occupation in which they have a “comparative advantage” depending on the amount of the embodied skills.

Estimting the wage equation using Ordinary Least Squares regression (OLS)

Based on this self-selection issue, if one estimates the wage equation for occupation by OLS regression, there would be a “self-selection bias.” The observed sub-sample of wages belongs to those who already have chosen (self-selected) that specific occupation. The “selectivity” or self-selection bias raises this concern: Can we recover the population distribution for the random variable of interest (*e.g.* earnings of a specific occupation) for the entire population from what is observed in the data?

In general, the mean earnings of individuals in a particular career they have selected presumably is higher than the mean earnings observed potentially for all individuals in the population if all had chosen to work in the same profession. Self-selection has been at the core of econometrics and empirical economics for decades. The Roy model is a structural model of self-selection that has been used to control self-selection bias in a large class of applications.

The idea underlying this model has been very influential in analyzing many applications. The relevant literature emphasizes the importance of self-selection, skill heterogeneity, and latent skills in understanding individuals’ choices and outcomes. Some examples are: college attendance and occupational choice (Heckman et al., 1998; Keane & Wolpin, 1997; Willis & Rosen, 1979), public versus private sector (Dustmann & van Soest, 1998), immigration (Abramitzky, Boustan, & Eriksson, 2012; Borjas, 1987), uncertainty and inequality in labour earnings in the U.S. economy (Cunha & Heckman, 2007), health care (Chandra & Staiger, 2007), effect of redistribution on migration (Abramitzky, 2009), Optimal taxation

(Rothschild & Scheuer, 2013).

1.4.3 Empirical static Roy models

In a seminal paper, Willis and Rosen (1979) use an empirical analysis to find comparative advantage evidence. The authors incorporate "self-selection" in a multidimensional skillset along the Roy model.

Results of the paper

As fully explained in Appendix B.4, Willis and Rosen's model is essentially about sorting into college attendance and the importance of self-selection and comparative advantage. The authors find a positive selectivity bias for the initial earnings of college attendees. In other words, earnings patterns of observed college students show higher initial wages than the population's if all hypothetically selected college studies. This finding shows current college students' "comparative advantage" in pursuing college studies over high school graduates.

Also, the authors find a positive selectivity bias for the income growth rates of high school graduates. Put differently, the observed earnings patterns of high school graduates show higher growth rates than the population's if all individuals, hypothetically, prefer to remain as high school graduates. This "positive selection" among both categories of high school graduates and college attendees supports the role of comparative advantage in the schooling decision-making process.

The model presented in this section assumed that individuals were certain about completing the years of schooling chosen. The model was static because the optimal choice of schooling investment is derived by maximizing the individual's expected lifetime return to the investment made once and forever at the beginning of the schooling period.[15] However, in real life, individuals may face sequential resolution of uncertainty about returns to schooling. This sequential arrival of information implies that education decisions are made sequentially

[15] Another example of a static model is Willis (1986), which augmented Willis and Rosen (1979) by a set of occupation-specific abilities for college and high school-type occupations, respectively.

and should not be treated as a static choice problem made once in a lifetime (Heckman et al., 2006).

The following section introduces Discrete Choice Dynamic Programming (DCDP) that extends the earlier work to a dynamic setting. Individuals face a sequential decision problem. The current state of individuals determines current decisions, which affects current pay-offs and tomorrow's states of being and so on.

1.4.4 Empirical dynamic Roy models

Building on the early work types of skills, heterogeneity of individuals, self-selection and comparative advantage. Keane and Wolpin (1997) (henceforth KW(97)) develop the first DCDP model to combine schooling, working and occupational choices in a single framework. Using 11 years of data on a sample of young white men from the 1979 cohort of the U.S. National Longitudinal Survey of Youth (NLSY79), KW(97) developed and estimated a dynamic Roy model of the labour market and education where agents have multidimensional skills.

Building on the early work of Willis and Rosen, KW(97) provide a vital extension where schooling decisions and occupational choices are the results of a dynamic, sequential process by forward-looking individuals. Keane and Wolpin are outstanding scholars who first introduced and applied the "approximate solution method" in Keane and Wolpin (1994), henceforth KW(94). The KW(97)'s model is thoroughly explained in Appendix B.5.

Main finding of KW(97)

The main finding of KW(97) is that heterogeneity in unobserved skill and preference endowments at age 16 (the comparative advantages of "types" of individuals) is potentially an important source of school attainment, occupational choices, and later labour market outcomes.[16] Using estimated parameters, they simulate data and find individual endowments

[16] Table 12, p.509

explain about 90% of the variance of expected lifetime returns or utilities. More specifically, the authors calculate the expected alternative-specific value functions (Equations 122 and 123) as well as the expected discounted present value of the utility stream (Equation 121) for each type of individuals. They find that the between-type variance in expected lifetime utility accounts for 90 percent of the total variance.

It is very extreme to conclude that 90% of inequality in lifetime earnings could be attributed to their heterogeneity and could be predicted at age 16.[17] This result implicitly states that reducing tuition fees may not significantly affect types other than type one.

Other findings

Some of the other results of KW(97) are as follows. First, the authors find multiple returns to schooling for various occupations. They find a much higher return in the white-collar profession (7%) compared to blue-collar (2.4%) and military occupations (5.8%).[18] This finding is an improvement compared to Mincer's assumption that internal rates of return to each year of schooling are identical to all levels of education studies, shown as β_1 in Equation (4). Second, white-collar skills depreciate much more rapidly than blue-collar skills.[19] This notion is in line with the findings of other scholars that find the depreciation rate of college graduate workers in the data is higher than that of high school graduates (examples are: Athreya, Ionescu, Neelakantan, & Vidangos, 2019; Huggett, Ventura, & Yaron, 2006, 2011; Ionescu, 2009).

The third finding reveals a positive correlation between the expected present value of lifetime monetized utility and the family background, specifically parental income.[20,21] Fourth, the model predicts the effect of *ex-ante* policy evaluation (counterfactual policy changes) of a $2000 college annual tuition subsidy (almost 50% of estimated college costs in

[17] Sullivan (2010) finds a 56% of variation in lifetime utility across individuals due to their heterogeneity. The remaining 44% is attributed to random shocks to wages, non-pecuniary utility flows, the arrival of job matches and randomness in human capital improvement.

[18] Table 7, p.500

[19] Table 7, p.500

[20] Table 13, p.511

[21] This result is found by post-estimation and regression of type probabilities on family background variables.

1987 dollars) is to increase the high school graduation rate by 3.5 percentage points and the college graduation rate by 8.5 percentage points.[22]

Regarding the policy intervention, KW(97) concludes that if the type of students were observable, the subsidy could be targeted to more "able" students. The results show that the primary beneficiaries of financial aid, in terms of lifetime utility, are type one individuals who choose white-collar jobs and possess higher skill levels. They are the only type with a positive utility gain net of per capita cost of subsidies.

Similar to many other DCDP models on human capital investment and labour supply, the decision of schooling and labour supply are mutually exclusive alternatives. Individuals can not work while studying and do not invest in human capital accumulation during working periods. It is an essential issue because, generally, students partially cover their college costs by working during study periods, and workers accumulate capital during working periods through on-the-job training. The model does not include these two dimensions of a typical individual when studying in a college or working in the labour market: study-work intensive margins during school and human capital accumulation during working periods of the life cycle.[23]

In KW(97), states are recurrent, meaning individuals can leave and return to their previous states. For example, an agent who has already dropped out can return to school. In other words, KW(97) permit individuals to move freely between schooling and other alternatives, such as working and staying at home. This feature is rarely observed in the data. Without a doubt, KW(97)'s model is original in many aspects. First, the model is developed in a multiple-skill framework. Second, both schooling and work experience accumulation in various occupations is endogenous. Following KW(97), several scholars estimated dynamic structural models of schooling decisions. Their papers assume that individuals form rational

[22]Table 14, p.513

[23]In some DCDP papers, the models allow individuals to work and enroll in school simultaneously, but they typically do not allow individuals to choose the intensity of their schooling. Instead, they let individuals choose full-time and part-time alternatives (See Eckstein & Wolpin, 1999; Keane & Wolpin, 2001, as examples). These modifications break choices into sub-choices (such as part- and full-time working), which results in a higher dimension of state space and, consequently much higher level of the computational cost of estimation.

expectations about their future earnings conditional on schooling decisions and that, in turn, the expected earnings affect their educational choices (see, for example, Belzil & Hansen, 2002; Eckstein & Wolpin, 1999; Keane & Wolpin, 2000, 2001; Lee, 2005).

Keane and Wolpin (2000) develop a model identical to that of KW(97) and evaluate the effect of two monetary incentives (school-bonus and wage-subsidy schemes) on closing the racial gap in graduation rate and U.S. labour-market earnings.[24] They estimate a model of schooling, work, and occupational choice decisions over the life cycle to investigate black/white disparity in educational attainment and earnings of American males.

The authors find that the primary explanation for the low schooling attainments of blacks relative to whites is the differences in initial skill endowments at age 16. Keane and Wolpin (2000) assess the impact of policies intended to close the racial gaps. They implement a scheme to equalize the schooling distributions of black and white males through financial incentives for black youth to continue in school. Analyzing the influence of such incentives on subsequent educational and labour market outcomes, the authors show that this policy has substantial responses in school completion levels of black youth but only a minimal effect on the racial earnings gap due to differences in skill (ability) endowments at age 16.

KW(97) and Eckstein and Wolpin (1999) pioneered the estimation of DCDP models for analyzing schooling choices. Their models have features in common with some other papers coming afterwards. Aguirregabiria and Mira (2010) group all such models under the label *Eckstein-Keane-Wolpin (EKW)* models after the authors who are the main contributors. The main features of *EKW* models are: allowing for permanent unobserved heterogeneity, non-additive shocks in occupation reward functions, the correlation across choices, and observable but choice-censored payoffs.

[24]The school-bonus plan was advocated in 1998 by Robert Bernard Reich, an American economist, professor, author, lawyer, and political commentator. The plan provides a $25,000 bonus for high school graduation to all youths whose parents earn less than 120% of the median household income. The wage subsidy scheme targeted at low-wage workers in general, suggested by Phelps (1997), provides an indirect subsidy (through firms) to workers with wages below a fixed amount. These schemes aim to equalize black and white males' schooling and earnings distributions.

1.5 Sequential learning models (information revelation)

The previous models assumed that some endowments of individuals, such as abilities and tastes, remain constant over the life cycle. In other words, educational choices are made with certainty and complete information. Some literature questions this assumption and explains that although the information is publicly available, educational decisions are made under uncertainty and incomplete or incorrect information. For example, Cunha, Heckman, and Navarro (2005) decompose wage variability into heterogeneity (which is known when schooling decisions are made) and uncertainty (or shocks, which is not known *ex-ante*). They conclude that uncertainty is empirically significant; Almost 30 percent of people would change their schooling decisions if they had perfect information.

Some scholars acknowledge that students' initial beliefs about the financial costs and benefits of different educational options are imperfect. More specifically, students who overestimate costs are less likely to enroll in any degree program and more likely to drop out. Also, individuals who overestimate earnings are more likely to default on student loans (Hastings, Neilson, Ramirez, & Zimmerman, 2016); students may not be initially aware of their preferences and abilities (Altonji, Blom, & Meghir, 2012), or individuals have different predictions of future earnings due to the lack of information (Wiswall & Zafar, 2015b).

Experimental research shows that providing detailed information on college majors, monetary incentives, and graduation outcomes helps students make better educational choices. These types of informational interventions could be considered fruitful policies to make students more ready for college and encourage them to put enough effort at earlier stages of schooling (see Herbaut & Geven, 2019, for a review). For example, Oreopoulos and Ford (2019) evaluate a school-wide randomized intervention program that provides in-person support to complete college applications to students at low-transition schools. The results show that among all Grade 12 graduates, the program increased the two-year college enrollment rates by about five percentage points. Furthermore, other studies show in-person college access interventions significantly affect four-year enrollment among disadvantaged students (for more detailed reviews of this literature, see Page and Scott-Clayton 2016 and French and Oreopoulos 2017).

Along the same line, many scholars highlight the importance of (learning) information in education; prospective college students must have correct perceptions about the level of preparation necessary to succeed in college. They suggest that students update their beliefs in response to academic performance. Students may update their beliefs about their ability or taste by considering their course grades, especially during the first years of college coursework. Grades signal the effort required to complete a degree in a given field.

There is a strand of literature addressing this problem of incomplete and uncertain information about individuals' tastes, abilities or expectations about future outcomes. Their approach follows the idea that young individuals have only imperfect knowledge and update it based on new information, such as performance and course grades in school courses. In these models, agents learn about their preferences and abilities sequentially. Also, they may update their expectations about their labour market returns from graduating with the majors. Consequently, they may change their choices in different periods. These learning (and updating) features make this strand of literature suitable to be named as ***sequential learning models***. This section introduces some of the pioneers' studies using these types of multi-stage learning models.

Altonji (1993) introduces a sequential learning model of college education where the college completion probabilities are *ex-ante* uncertain. In this simple two-period model, individuals learn about future earnings and preferences over three educational choices. As a result, they may change their decisions when acquiring this new information.

More specifically, at the end of the first period, students may change their major or drop out of school. The choice depends on the individuals' ability, their stock of knowledge accumulated in the first year, the probability that an individual will ultimately complete a particular level of education in a specific field if they attend college, and the payoffs associated with the different educational outcomes, and the new information about their tastes for schooling.

Altonji's model is described in Appendix B.6. This model is considered the most crucial theoretical reference for understanding and analyzing the rationale behind choosing to drop out of university. Further studies developed their model based on this seminal paper. Montmarquette, Cannings, and Mahseredjian (2002) extend the Altonji's model by allowing the completion probabilities to vary across individuals and majors. They define p_{ij} as the perceived probability of success of individual i in major j. y_{ij} is the earnings individual i expects by graduating in major j. They also assume that the expected utility of individual i choosing major j depends on expected earnings,

$$\mathbb{E}(U_{ij}) = p_{ij}(x)y_{ij}(z) + \Big(1 - p_{ij}(x)\Big)y_{i0}(z), \quad i = 1, \dots, N, \quad j = 1, \dots, m, \tag{15}$$

where x and z influence the probability of success and earnings of graduates, respectively. y_{i0} is the earnings alternative with no success in any major. Then, an individual i will choose j over the alternative k if

$$\mathbb{E}(U_{ij}) - \mathbb{E}(U_{ik}) \geq 0. \tag{16}$$

Expanding Equation (16) based on definition given in Equation (15) and adding and subtracting $p_{ij}(x)y_{ik}(z)$ to both sides of it results in

$$p_{ij}(x)\Big(y_{ij}(z) - y_{ik}(z)\Big) + \Big(p_{ij}(x) - p_{ik}(x)\Big)\Big(y_{ik}(z) - y_{i0}(z)\Big) \geq 0. \tag{17}$$

Based on Equation (17), authors state that if the perceived probability of success of individual i in major j substantially differs from that of major k, $\Big(p_{ij}(x) - p_{ik}(x)\Big) >> 0$, then this difference could play an essential role in choosing major j. But, if the perceived probabilities are almost equal ($p_{ij}(x) \cong p_{ik}(x)$), then the primary determinant of choosing a major is the earnings difference in occupations expected from the two majors, $y_{ij}(z) - y_{ik}(z)$. For example, for very talented students, the probability of success is almost equal and high in all majors; therefore, earnings at graduation should matter more than the probability of success.

Then, the authors define a latent variable as the expected level of indirect utility, expressed as a linear function of the individual's expected earnings and normalized by the characteristics of the individual and an unobserved random component. Using this latent variable and mixed multinomial logit model, they estimate the perceived probability of success of individual i in major j and other relevant parameters. They use data from the National Longitudinal Survey of Youth (NLSY) and estimate the model with mixed multinomial logit and probit models and a heteroscedastic extreme value model. Estimating the effect of expected earnings on college major choice, Montmarquette et al. find that choosing a college major depends effectively on the expected earnings in a particular major. Also, they find that the expected earnings play a more important role for males than females and nonwhites than whites in the context of college major choice.

Altonji et al. (2012) provides a dynamic model of education and occupation choice in which innate ability and preferences are unknown to the individuals who learn about these endowments through college environment and work experiences, such as trying a set of courses or switching occupations in the labour market.[25] Their model, similar to Altonji's model, implies an essential distinction between the *ex-ante* and *ex-post* returns to education decisions and their effects on educational choices.

The theoretical model of Arcidiacono (2004) is similar to Altonji's model, but he also includes learning about major-specific abilities. Arcidiacono develops and estimates a multi-stage sequential college and major choice model where individuals are forward-looking and uncertain about preferences, ability, and labour market opportunities.

His dynamic model has three periods. In the first period, agents choose a college major in a specific college or decide to enter the labour force. In the second period, individuals receive new information about their abilities (through grade point averages) and tastes (through preference shocks).[26] With this new information, individuals update their decisions by changing their college major, college, or entering the labour force. Agents choose the option

[25] The authors also review the literature on the demand for and return to high school and post-secondary education by field of study.

[26] The first period is a proxy for the first two years, and the second period is for the remaining two years of college studies.

that yields the highest present value of lifetime utility. In the third period, all individuals work with no other decisions.

These dynamics allow for learning about one's abilities through grades. Those who perform worse than expected may find it more attractive to drop out or switch to a less complicated major. To control for unobserved heterogeneity, similar to KW(97) and Eckstein and Wolpin (1999), the author considers multiple types of individuals and uses finite mixture distributions of types. Individuals are supposed to know their type, which the econometrician does not observe. Estimation of parameters is based on the Expectation-Maximization (EM) algorithm, which makes the two-step partial likelihood approach compatible with the finite mixture model.[27]

The author aggregates majors into four categories: Natural Sciences (including Math and Engineering), Business (including Economics), Social Science/Humanities/Other, and Education.[28] The model is estimated using the National Longitudinal Study of the Class of 1972 (NLS72).[29] Descriptive analysis of the data reveals that average scores on Math and verbal tests in majors with higher future earnings (such as Natural Sciences) are higher than lower-paid majors (*e.g.* Education). This analysis shows that higher-ability students self-select themselves into more lucrative majors.[30] Also, the data shows that students update their choice of major over time. For example, on average, those who switch from more lucrative majors to less lucrative ones have lower Math abilities.

Estimation results indicate three critical points. First, math ability is much more important in explaining the college major choice than verbal ability. Second, learning about ability is essential in switching majors or dropping out of college. Finally, most ability sorting across majors appears to be driven by the preference heterogeneity over the various majors.

[27]This algorithm is developed in Dempster, Laird, and Rubin (1977) and adapted to DCDP model by Arcidiacono and Jones (2003) which shows that the EM method produces consistent estimates of the parameters with considerable computational savings.

[28]The aggregation criteria is the degree of similarity in mean earnings, SAT Math and verbal scores.

[29]NLS72 is a nationally representative, longitudinal study of 12th graders in 1972 with follow-up surveys in 1972, 1973, 1974, 1976, 1979, and 1986. The focus of NLS72 is to determine individuals' postsecondary educational and career outcomes after leaving high school. Source: Source: U.S. Department of Education, National Center for Education Statistics (NCES), NLS-72, (last accessed December 2023).

[30]Tables 1, p.4 and Table 2, p.6

Arcidiacono (2005) develops and estimates a sequential dynamic model to study how changing the admission and financial aid rules at colleges in favour of non-white applicants (affirmative actions) affects their educational decisions: where to submit applications and, conditional on being accepted, in which college to enroll and what major to study. The decisions affect individuals' future earnings.[31]

The model comprises four stages: submitting applications by prospective students, admissions and financial aid decisions by schools, the decision of individuals (whether to join the labour market or which school to attend and what field to study to pursue), and the final working stage for those who graduate. Individuals make application decisions based on their expectations of the probability of acceptance, the cost of the application, the expected financial aid, and how well they will like a college-major combination.

In this model, individuals' expected utility is equated to the log of the expected present value of lifetime earnings. As the primary data source, the model is estimated using panel data on high school graduates from a single cohort, the National Longitudinal Study of the Class of 1972 (NLS72). The author aggregates majors precisely in the same manner as in Arcidiacono (2004) and with the same number of choices available for individuals. Parameters are estimated by the Expectation-Maximization (EM) algorithm, and to control for unobserved heterogeneity, the author uses finite mixture distributions of types of individuals.

The author uses the model to examine the reasons for significant earnings and ability differences across college majors. He finds that cognitive (Math) ability is an essential determinant of college major choice, and students with a major in natural sciences indeed have significantly higher test (SAT) scores in mathematics as well as in verbal tests than their peers in the other fields. Arcidiacono (2005) also investigates the impacts of affirmative action on Black admissions and future earnings. The result of simulations shows that removing Blacks' advantages in admissions and financial aid substantially reduces the number of Africans as the primary data source.

[31] In the U.S., affirmative actions positively affect the admission of racial minorities and the amount of financial aid they will receive in college.

Using longitudinal data from the NLSY97, Arcidiacono, Aucejo, Maurel, and Ransom (2016) estimate a dynamic model of college attendance, major choice and work decisions where individuals are uncertain about their schooling ability and labour market productivity. At the end of each year, individuals update their ability and productivity beliefs through college grades and wages. The authors find that a sizable share of the dispersion in college grades and wages is accounted for by the ability components that are initially unknown to the individuals. They state that if individuals have perfect information on their abilities by the end of high school, then, relative to their baseline model, the college graduates would increase by around nine percentage points, almost all by a decrease in dropout rates.

In the spirit of Altonji (1993), Altonji, Arcidiacono, and Maurel (2016) provide a three-period model of education choice to demonstrate how uncertainty about an agent's cognitive abilities influences the dynamics of major choice. Agents sequentially choose their schooling and occupational decisions to maximize the discounted sum of their payoffs in three periods. An exciting implication of the model is obtained by including a non-pecuniary element in the utility; individuals may value job satisfaction more than the potential wage from the job. For example, an individual may choose an economics major over medicine because they may get a very high level of non-pecuniary satisfaction by working as a professor in Economics compared to a doctor, even though their income is way lower than doctors.

All papers reviewed up to this point were based on *"Rational Expectation"* (RE) approach using observed data on choices and earnings, either with or without sequential learning. The following section will discuss more papers in which the *Rational Expectation* assumption is relaxed. By following this approach, in place of using observed data, researchers use datasets derived by eliciting individuals' beliefs about various outcomes, called *subjective data.*

1.6 Subjective expectations data framework (eliciting students' expectations)

Economists have long noticed the importance of expectations to individuals' educational choices. The models explained so far are based on *Rational Expectation*, which assumes agents have complete information about the problem's deterministic features and rational expectations over stochastic features meaning that the agents' subjective belief distribution of a given stochastic feature (such as earnings) will be equivalent to the 'objective' (model) distribution of that feature.[32]

The theory of Rational Expectation states that agents have expectations that do not systematically differ from the realized outcomes. Based on the Rational Expectation assumption, the standard practice of economists has been to infer decision processes from data on *observed choices* and ***realized outcomes*** such as earnings (Manski, 2004).[33] This approach may deliver an excellent approximation to reality and provide a convenient assumption that helps to impose a degree of internal consistency on the model. For example, identifying the utility of attending school might be resolved using realized post-schooling wage data inside the value functions.

However, there are some critiques of Rational Expectation, and some scholars question the empirical validity of this approach. Manski (1993, 2004) depart from the rational expectations assumption by highlighting the importance of an individual's subjective expectations about future earnings. He concludes that the only hope for understanding college choice and labour market returns on schooling is the collection and analysis of ***subjective data*** on students' expectations.

Manski argues that individuals forming expectations face an inferential problem in using

[32] Under the Rational Expectation approach, individuals know the accurate parameters of the model and all future conditional wage distributions and apply the knowledge of the true income-generating process to forecast future personal income. But of course, individuals do not have the perfect foresight and do not know the particular wage draws they will obtain from these distributions.

[33] This standard practice is often called *revealed preference analysis*.

prior knowledge and available data to learn features of a probability distribution of interest. Individuals may possess different data on realized events, have different prior knowledge of the environment, and process their information differently. The author states two fundamental and interrelated identification problems. "*The first problem is that not knowing how youth perceive the returns to schooling, one cannot infer their decision processes from their schooling choices. (...) The most that one can do is infer the decision rule conditional on maintained assumptions on expectations.*" (Manski, 1993, pp.44-45).

In other words, observing individuals' choices does not reveal the distribution of underlying primitives because observed choices might be compatible with multiple configurations of preferences over outcomes and expectations (Giustinelli & Manski, 2018; Manski, 2004). "*The second problem is that not knowing youth's decision processes, one cannot infer the objective returns to schooling from data on realized outcomes. (...) Hence, one can only infer the objective returns to schooling conditional on the validity of expectations assumptions.*" (Manski, 1993, p.45). Put differently, "*identification of decision processes from choice data must rest on strong maintained assumptions.* "(Manski, 2004, p.1330). Manski also questions the empirical relevance of Rational Expectations: "*If experts disagree on the returns to schooling, is it plausible that youth have rational expectations? I think not*" (Manski, 2004, p. 1336).[34]

Using subjective data (based on personal expectations) or observed data (under a Rational Expectation framework), which one is a valid predictor of future outcomes?

On one side, some scholars find a close relationship between data on earnings beliefs and subjective probabilities with realized outcomes. Wiswall and Zafar (2021) followed the students over time by conducting a follow-up survey six years after the initial data collection. Investigating the future outcomes, they find a close connection between these realizations and the subjective expectations of these outcomes. Also, Arcidiacono, Hotz,

[34]The agents' behaviour may also be perceived as decisions with *"bounded rationality"*, which means that they lack the computational or analytical ability required to make fully rational decisions. They "think" that their decisions are the best decisions for themselves (based on what they know about true parameters and the income-generating process.)

Maurel, and Romano (2020) use elicited-beliefs data from a sample of individuals who were first interviewed as undergraduate students at Duke University and followed up seven years later. The authors then compare subjective beliefs with realized labour market outcomes. They find that data on earnings beliefs and subjective probabilities of working in particular occupations are highly predictive of actual future earnings and occupational choices.

Furthermore, Gong, Stinebrickner, and Stinebrickner (2020) use the ten-year annual post-college survey and compare the actual labour supply, marriage, and children outcomes with the correspondent in-school survey of elicited beliefs. More specifically, they compare the average reported probability of having a particular outcome to the fraction of individuals with that outcome. The authors show that people have realistic expectations regarding their future work and family life. For example, the average perceived probability of working full-time at age 28 is 66.6% for women and 81.6% for men. However, they find that beliefs about marriage and children are not as accurate as beliefs about labour supply.

Conversely, multiple studies doubt the strong relationship between the realized outputs and subjective data. d'Haultfoeuille, Gaillac, and Maurel (2018, 2021) introduce new tests of rational expectations based on the marginal distributions of realizations and personal beliefs and question the rationality of agents' beliefs demonstrated in the subjective expectations data. Complementing these tests and using data from the Berea Panel Study (BPS), Crossley, Gong, Stinebrickner, and Stinebrickner (2021) propose new tests of Rational Expectations to study the validity of young adults' beliefs about their future incomes.[35] They apply these tests to data on income expectations and realizations from the BPS. Their new tests reject *ex-ante* Rational Expectations for college students. Also, they find that individuals' beliefs about future income become more *ex-ante* accurate when students have graduated, and most have had their first experience in the labourer market. Furthermore, Crossley, Gong, Stinebrickner, and Stinebrickner (2022) show that beliefs may be rational but suffer from considerable subjective uncertainty because economic agents may have little

[35] The The Berea Panel Study (BPS) launched by Ralph and Todd Stinebrickner is a landmark among existing surveys of students' expectations. Following two cohorts of Berea College first-year students for up to fourteen years, the BPS collects rich information on the expectations and realizations of students' education and labour market outcomes during and after college.

relevant information about future events. Also, a population of agents with Rational Expectations may be affected by aggregate shocks. Therefore their beliefs about future outcomes lose accuracy and validity.

As discussed above, controversial arguments exist about the validity of these two approaches in forming expectations and usage of the desired data, and it is still an open question. The following explains some studies using subjective data under the subjective expectation approach.

Papers on "subjective data"

A growing literature on educational and career choices uses individuals' elicited beliefs and leverages subjective expectation data to understand decision-making under uncertainty. These pieces of literature relax the assumption of rational expectations and collect personal expectations for future outcomes in different regimes. They obtain individuals' expectations about factual and counterfactual results by asking about various college major choices. This literature includes (but is not limited to) Zafar (2011, 2013); Kaufmann (2014); Delavande (2014); Stinebrickner and Stinebrickner (2003, 2004, 2008a, 2008b, 2011, 2012, 2014a, 2014b); Giustinelli (2016); Wiswall and Zafar (2015a, 2015b, 2018, 2021); Arcidiacono, Hotz, and Kang (2012); Attanasio and Kaufmann (2014, 2017); Baker, Bettinger, Jacob, and Marinescu (2018); Delavande and Zafar (2019); Gong, Stinebrickner, and Stinebrickner (2019); Gong et al. (2020); Arcidiacono, Hotz, Maurel, and Romano (2014); Arcidiacono et al. (2020); Patnaik, Venator, Wiswall, and Zafar (2020); and Conlon (2021) (for surveys on information provision experiments, see Fuster & Zafar, 2022; Haaland, Roth, & Wohlfart, 2022; Patnaik, Wiswall, & Zafar, 2020).

The earliest attempt I am aware of that collects subjective expectations data in the context of college majors is the Berea Panel Study (BPS), starting in the early 2000s, which collected detailed information from Berea College students in central Kentucky. The BPS follows two cohorts of students from college entrance to age 30. Each year, the study elicited each student's beliefs about post-college income at particular future points in time. Subsequently, the study also collected each student's actual realized earnings at those same points in time. Stinebrickner and Stinebrickner (2003, 2004, 2008a, 2008b, 2011, 2012, 2014a, 2014b) use these subjective expectations data from Berea College and examine the relationship between working during school, study effort, and academic performance, the college major change, and dropouts for college students. They provide direct evidence that learning about schooling ability is a major determinant of a college dropout. The authors find that 40 percent of all dropouts should be attributed to what students learn about their academic ability/performance.[36]

Introducing various relevant studies, this section explains one paper in more detail. Wiswall and Zafar (2015a) use a methodological innovation in their "information intervention field experiment".[37] They aim to separate the effects of two components on the probability of choosing a college major: the major-specific taste component and the beliefs about future earnings. More specifically, they use sequential surveys and incorporate subjective expectations into models of choice behaviour. They try to understand how providing objective information on returns to schooling alters students' beliefs about their future, such as educational choices, earnings, labour supply, marital status, and spousal characteristics.

In this regard, the authors follow a survey-field experiment approach to elicit and re-elicit the "beliefs" of undergraduate students.[38] They collect data on expectations for the chosen and counterfactual alternatives and incorporate subjective expectations into the choice behaviour model. The experiment data is from an original survey instrument administered to New York University (NYU) undergraduate students from May to June 2010. The study was limited to full-time NYU students in their freshman, sophomore, or junior years, at least 18 years of age, and U.S. citizens.[39]

[36]Their primary research question to specify the determinant of school dropout is similar to that of Eckstein and Wolpin (1999), but in the college context.

[37]Their approach is in line with a growing literature that uses survey experiments to study the expectation formation process focused on inflation expectations (see, for example, Coibion, Gorodnichenko, & Ropele, 2020; Roth & Wohlfart, 2020) and house prices (Armona, FusterAndreas, & Fuster, 2019; Fuster, Perez-Truglia, Wiederholt, & Zafar, 2018, as examples).

[38]The model assumes that individuals may make decisions that are not in their best interests when they are young. College students need to be more informed about salaries conditional on college majors. They may update their beliefs and decisions over time. On average, over half of the estimated models of college major choice find that learning about actual salaries occurs in the final year of college studies (Betts, 1996).

[39]The educational system in the U.S. is such that students of a four-year college in most schools only choose their majors at the end of year two or even sometimes year three.

The authors refer to these beliefs as "self" beliefs, *e.g.* students' beliefs about their earnings after graduation with a specific degree, distinct from the "population" beliefs *e.g.* students' beliefs about the average earnings in the population for individuals who graduate with the same degree. In other words, beliefs are individual-specific and may not be consistent with rational expectations.

The experiment was done in two stages. In the first round, to elicit students' "baseline beliefs" conditional on each major, they are asked about their beliefs about their abilities, self-earnings, the probability of marriage, labour supply, spouse's earnings and labour supply.[40] This information is just for two or three points in time after graduation, immediately after graduation, at the age of 30 and 45. Then, the authors use various polynomial approximations to interpolate between data points by age and use a normal distribution to approximate the distribution of beliefs and create experimentally derived subjective expectations panel data to be used in modelling the choices of individuals.

In the second round, students are provided "objective" information such as the average earnings of the population across a broad set of occupations and majors and asked again about their "updated beliefs". The information comes from the Current Population Survey (CPS) taken from the March 2009 survey and the 2003 National Survey of College Graduates (NSCG). The experimental design creates panel data for major choices and the expected earnings. Wiswall and Zafar's model is fully explained in the supplementary appendix titled Appendix B.7.

Main finding of the paper

The paper's main finding is that the dominant factor in choosing a college major is the unobserved heterogeneity, such as "tastes" of individuals for majors and the perceived "abilities" in those majors, explaining about 91% of the choice of a major.[41] The rest are explained by the financial incentives (the beliefs concerning expected earnings). This result is similar to the result of Keane and Wolpin (1997) that states 90% of inequality in lifetime

[40] probabilities with $\pi_k \in [0,1]$, for all k, and $\sum_{k=1}^{K} \pi_k = 1$.
[41] Table 6 p.813: (1.613-0.146)/1.613*100% = 91%

earnings could be attributed to individuals' heterogeneity as it is already discussed in this chapter in Section 1.4.4 (main finding of KW97).

Remarks

It is essential to notice that this result does not come from estimating a structural parameter from the utility function. Furthermore, the survey sample is limited to a particular sub-population of high-income high-ability undergraduate students of an elite top school. It is not a good representative of the universities in the U.S.

Using the same dataset of Wiswall and Zafar, NYU, and a set of hypothetical survey questions to elicit students' preferences over risk and self-control, Patnaik, Venator, et al. (2020) apply a methodological innovation. They use these individual-specific measures on time and risk preferences to identify each individual's discount factor and coefficient of risk aversion. They estimate a general life cycle model to explore the importance of risk aversion, impatience, and earnings expectations in choosing a college major. The results show that women, on average, are more risk-averse and patient than men. Also, the model shows that earnings expectations play a role in the choice of majors, but this role is small compared to the non-pecuniary aspects of the major for most students.

Zafar (2011) was the first to use beliefs about earnings in both actual and counterfactual majors to see how expected earnings affect college major choices. He collects a panel dataset of Northwestern University sophomore undergraduates that contains their subjective expectations about major-specific outcomes. The author finds that students have biased beliefs about their major-specific abilities. He examines how and why college students revise their expectations about outcomes related to their choice of major. The updating process is found to be consistent with the Bayesian learning model.

Related to Zafar (2011), the study of Arcidiacono et al. (2012) is about estimating a model of college major choice that incorporates subjective expectations and assessments using a survey.[42] This survey was administered by authors at Duke University in 2009. The authors

[42]The survey designs in Zafar (2011) and Arcidiacono et al. (2012) are somehow different. While the former design asks students to provide expected earnings conditional only on majors, the latter asks for their

collected data on background characteristics and male undergraduate students' current or intended major in this survey. The authors elicited students' subjective assessments of their expected abilities in chosen and counterfactual majors. They included students from all classes (i.e., first-year students, sophomores, juniors, and seniors).

The authors divide the majors into six broad groups: natural science, humanities, engineering, social sciences, economics, and policy. Also, they use six broad career groups to characterize possible careers: science/technology, health, business, government/non-profit, education, and law. To examine the potential role of future expected earnings on these choices, the authors asked students about their subjective expectations on some items: the probabilities of entering different careers/occupations, the earnings associated with various careers ten years after graduation conditional on both their own major as well as on majors they do not choose, i.e., their *counterfactual* expectations.

According to the research by Arcidiacono et al., while both ability and anticipated earnings play crucial roles in selecting a major, the significance of expected earnings persists even after controlling for ability and career preferences. For instance, in their model, if the abilities of individuals were to be equalized, there would be a substantial increase in the number of students opting for Economics as their major, alongside a decline in those choosing Humanities. The former major tends to align more closely with business-oriented occupations that promise elevated anticipated earnings, whereas the latter predicts a comparatively lower future income trajectory.

Also, the authors show how the students' misinformation or informational differences on market returns affect their choice of major. They notice that students' expectations about the future can differ because they make errors in their forecasts of future earnings. They asked each student to assess what the "average" Duke (male) undergraduate would earn in different major–career combinations. The authors find a wide range of the students' forecasts. Then, they eliminate differences across students in their projections about the

expected earnings for various majors and subsequent career combinations. In the former survey, there is no restriction on gender, while in the latter, the respondents are only male students. Furthermore, the latest survey covers more students from different levels of study, while the former covers only sophomore students.

average Duke students and estimate how it would have changed students' choice of a major. The findings of the new estimation suggest that 7.8% of students would have chosen different majors had they had correct measurements of population returns. This number shows how choices would have differed from the status quo accurate information.

Using a similar methodology, Zafar (2013) uses subjective expectations data and focuses on gender differences in choosing a major. He studies the college major choice of Northwestern University from a dataset that contains subjective expectations about choice-specific outcomes. The survey was administered to undergraduate students at Northwestern University in the early part of their sophomore year from November 2006 to February 2007.[43]

The author finds that different gender preferences for non-pecuniary components can explain gender differences in college majors' enrollment. Examples of these components are enjoying coursework, working at potential jobs, work-life balance, and gaining parents' approval. He shows that men are attracted to majors and careers that offer extrinsic rewards, such as economic returns, whereas women value intrinsic rewards more. Non-pecuniary outcomes explain more than three-fourths of female choices.

Also, the author finds that most of the gender gap in STEM enrollments at the tertiary level is driven by differences in tastes and preferences, not because of discrimination or differences in academic preparation. To narrow the gap, he concludes "a possible policy implication . . . is to encourage policies that increase the representation of females in academic science and engineering, since these female professors may change female students' beliefs and preferences toward example using hypothetical choice experiment".[44,45]

[43] Zafar denotes this survey as the *Fall 2006* or *initial* survey. Zafar (2011) uses both *initial* and a second survey which was administered to a subset of the initial survey takers at the beginning of their junior year when students had presumably settled on their final majors (Northwestern University requires students to officially declare their majors by the beginning of their junior year). The second survey spanned the period from November 2007 to February 2008. Zafar denotes it as the *Fall 2007* or *follow-up* survey.

[44] p.585

[45] The result is in line with the literature that explains the widening of the gender gap in major choices by differences in tastes/preferences. For example, Gemici and Wiswall (2014) find that, because of higher expected future labour supply, males have been more responsive to the increase in demand for science and business degrees in the 1980s and 1990s, leading to a widening of the gender gap in major choice. (see more examples using hypothetical choice experiment, Gelblum, 2020; Wiswall & Zafar, 2018, 2021).

Inspired by the approach and methodology used by Blass, Lach, and Manski (2010) and Wiswall and Zafar (2015a) for four-year college students, Baker et al. (2018) study two-year community colleges. They find that taste and course enjoyment is the most important predictor of college major choice, and extrinsic rewards are less critical. For example, the expected wage has a positive but weaker relationship with a major choice. Also, the relationship between the probability of employment and college major choice is not statistically significant.

Wiswall and Zafar (2021) aim to answer the following question: Are individuals motivated to invest in schooling motivated by future family-related incentives and not just their future labour income? These "family" incentives are the future spouse's income, workplace hours, flexibility, accommodation for raising children, and fertility.[46] The authors surveyed current undergraduate students at New York University (NYU) from May to June 2010.[47] The survey was about the student's perceptions of the career and family consequences of their educational choices, including earnings, labour supply, the likelihood of marriage, characteristics of their future spouses, and the number of children they expected, conditional on a set of majors to choose from.

Authors aggregated college major choices into five categories: (1) business and economics, (2) engineering and computer science, (3) humanities and other social sciences, (4) natural sciences and math, and (5) never graduate/drop out. Similar to Wiswall and Zafar (2015a), they use a survey consisting of three distinct stages: eliciting beliefs, feeding some information, and re-eliciting beliefs of students and the questions about the future were conditioned on three particular future points in time: immediately after graduation (approximately age 23), at age 30, and at age 45.[48]

Wiswall and Zafar (2021) find that individuals (women, in particular) make human capital

[46] Their approach is closest to that of Arcidiacono et al. (2020), who elicit beliefs about earnings associated with counterfactual choices of college majors and occupations from Duke University undergraduate students.

[47] The study was limited to full-time NYU students who were in their freshman, sophomore, or junior year, at least 18 years of age and US citizens.

[48] To provide some evidence about the "reliability" of these subjective data, in a follow-up survey, nearly six years after the original data collection, the authors investigate whether expectations are predictive of actual future outcomes, and they find a close connection between beliefs and outcomes.

choices based on their expected earnings and the future "family" life aspects. The authors claim that "family" outcomes can help to understand the black box of *tastes* as a determinant for college choice. Also, it can potentially shed light on the causes of the underlying gender gap in major choices. Also, the authors show that students sort into majors based on comparative advantage in terms of perceived abilities and *ex-ante* returns. For example, they find that students majoring in the sciences/business perceive higher expected returns (for themselves and their spouses) and higher relative ability rank in the sciences/ business versus the humanities compared to their counterparts.

Some studies explore how exposing new information other than expected earnings can change college major choices. Fricke, Grogger, and Steinmayr (2015) exploit an experiment and find that first-year college exposure to specific fields of study contents affects later college major choice. They exercised a natural experiment in Switzerland, where first-year students are randomly assigned to write a research paper in either business, economics or law. Assignment to the economics treatment group increased the choice of the economics major substantially. Furthermore, individuals may not even know what options are available, which may significantly impact their choices, especially for low-income students (Hoxby & Avery, 2013; Hoxby & Turner, 2015).[49]

1.7 Historical trends in educational choices in the United States

As explained in the Introduction part of this dissertation, one of the most remarkable changes in the U.S. labour market in the past decades has been the increase in the educational attainment of its labour force. From a historical view, this substantial and well-documented expansion of schooling started in the early 1900s. Also, the twentieth century witnessed

[49]See Patterson, Pope, and Feudo (2019); Arcidiacono, Aucejo, and Hotz (2016), and Bordon and Fu (2015) as similar studies exploring the effects of other types of information revelation on college major choices.

a significant increase in college-high school wage premiums.[50,51] This section introduces some scholars' points of view regarding these two historical trends and their relationship with changes happening for factors such as individuals' learning ability, human capital, and family backgrounds in the context of the United States labour market during the twentieth century.[52,53]

1.7.1 Expansion in the mean ability gap over the years

Hendricks and Schoellman (2014) focus on a dramatic change in the structure of U.S. education in the past decades, that is, an increase in test score gaps between college-bound and non-college-bound students. Their main idea is that this trend has changed the composition of cognitive abilities by educational attainment for different cohorts. The average ability level of college graduates is likely increased compared to that of high school graduates for the recent cohorts. Also, the authors notice a remarkable increase in the college wage premium gap over the past decades. In this regard, the authors develop a modified human capital model to deliver a higher monetary return for college graduates to justify the growing trend in the college wage gap.

As the first contribution of their paper, the authors provide extensive documentation on the divergence of test scores (as a proxy for ability) between two groups: (1) college-goers or college-bound high school seniors (either graduate from college or not) and (2) college non-goers or non-college-bound high school seniors (either graduate from high school or not).

[50] The college-high school wage premium is defined as the median hourly wage ratio for college graduates and those who only completed high school.

[51] See, also, Katz and Murphy (1992); Bound and Johnson (1992); Topel (1997); Katz and Autor (1999); Acemoglu, Aghion, and Violante (2001); Autor, Katz, and Kearney (2008); Goldin and Katz (2008); Acemoglu and Autor (2011); Restuccia and Vandenbroucke (2012); and Autor, Goldin, and Katz (2020), among others.

[52] See, for example, Athreya and Eberly (2021); Castro and Coen-Pirani (2016); Donovan and Herrington (2019); Hendricks et al. (2021); Hendricks and Schoellman (2014).

[53] Another strand of literature uses human capital theory and develops models to explain the educational attainment difference across countries and over time. They may also explain the role of human capital in determining the wealth of nations and explaining the income gap across countries. This type of literature is out of the scope of this dissertation. Examples are: Bils and Klenow (2000); Erosa, Koreshkova, and Restuccia (2010); Schoellman (2012); Restuccia and Vandenbroucke (2014); Manuelli and Seshadri (2014); among others.

They find a growing gap between the abilities of high school and college-educated workers in the data over the past decades. For the earliest cohorts of the 20th century, students who did not continue to college scored only ten percentage points lower than those who did. By the 1970s, that gap had grown to nearly thirty percentage points.

This observation suggests that differences in mean ability between college and high school graduates likely account for the increasing college wage premium gap over time. With this motivation, the authors develop a school choice model under ability heterogeneity and calibrate it to the National Longitudinal Study of Youth 1979 (NLSY79) dataset.[54] The environment is a discrete-time overlapping generation (OLG) model. Individuals are indexed by their birth year τ and their age ν. Each year a cohort of unit measures is born and lives for a fixed T period. The lifetime utility is given by

$$\sum_{\nu=1}^{T} \beta^{\nu} \ln c(q,\nu) - \frac{\chi(s,\tau)}{\exp(p+a)}, \tag{18}$$

where $\beta > 0$ is the common discount factor, ability represents by a, and preference or taste for schooling (s) is shown by p. The authors represent the type of an agent by $q = (a, p, \tau)$, their endowment (a, p) and their birth cohort, τ. $c(q, \nu)$ denotes the consumption of a person of type q at age ν, and $\chi(s, \tau)$ captures the psychic cost of schooling level, s, for cohort τ.[55] Schooling is distasteful, $\chi_s(s, \tau) > 0$, but less so for more able students or those with a higher taste for schooling.

Agents' budget constraint requires them to finance lifetime consumption through lifetime earnings. School attainment type s takes $T(s)$ years to complete. Individuals start to work right after schooling, $T(s) + 1$, and receive the relevant wages, $y(s, q, \nu)$ that depend on their school attainment (s), age (ν), and type (q). The higher-ability type agents receive higher

[54] Some other scholars also claim that the high difference between college and high school wages can not be explained only by the strict income maximization framework of standard human capital models. As one explanation: "people do not only (or even mainly) make their schooling decisions by looking at their monetary returns in terms of earnings. Psychic costs play a significant role. More able people have lower psychic costs of attending college." (Heckman et al., 2006, p.436).

[55] The schooling attainment (s) includes four exhaustive and mutually exclusive education categories: high school dropouts, high school graduates, some college, and college graduates.

wages. Budget constraint is defined as

$$\sum_{\nu=1}^{T} \frac{c(q,\nu)}{R^j} = \sum_{\nu=T(s)+1}^{T} \frac{y(s,q,\nu)}{R^\nu}, \tag{19}$$

where R is the exogenous interest rate. Also, the authors assume that wages are given by

$$\ln y(s,q,\nu) = \theta a + w(s, \underbrace{\tau+\nu-1}_{\text{current period}}) + h(s,\nu). \tag{20}$$

Wages have three components. θ captures the direct effect of ability on wages. w is the skill price or the price per unit of labour supplied by an agent, and $h(s,\nu)$ captures the human capital accumulated by workers of education s at age ν through experience or learning-by-doing.

Workers choose their school attainment, s, and consumption path, $c(q,\nu)$, to maximize preferences (18) subject to their budget constraint (19). The authors characterize the solution in two steps: First, they find the optimal allocation of consumption over time given school choice; then they find the school choice that maximizes lifetime utility.

Consumption in this model satisfies the standard Euler equation, $c(q,\nu+1) = \beta R c(q,\nu)$. By combining this equation with Equations (19) and (20), and then plugging into equation (18), the authors rewrite lifetime utility as an indirect utility function

$$\underbrace{\theta a \sum_{\nu=1}^{T} \beta^\nu}_{\text{effect of ability}} + \overbrace{\sum_{\nu=1}^{T} \beta^\nu \ln \left[\frac{R(\beta R)^{\nu-1}}{\sum_{j=1}^{T} \beta^{j-1}} \sum_{j=T(s)+1}^{T} \frac{e^{h(s,j)+w(s,\tau+j-1)}}{R^j} \right]}^{\text{indirect effect of schooling attainment}} - \underbrace{\frac{\chi(s,\tau)}{\exp(p+a)}}_{\substack{\text{direct effect} \\ \text{of schooling}}}.$$

To see how the choice of schooling, s, interacts with the agent's endowments, (p,a), one needs to investigate all three components of the indirect utility function in detail. The first term shows that the higher ability allows for higher lifetime utility (through increasing lifetime consumption). However, it does not interact with schooling choices, s. Therefore it drops out of the individual's optimization problem. The second term reveals that more years of schooling reduces the time in the labour market but also changes the skill price and the rate of human capital accumulation. It captures the indirect effect of school attainment on lifetime utility. However, this term does not interact with the initial endowments, either with a or with p.

Only in the last term does the choice of schooling directly affect lifetime utility. This term also shows an interaction of schooling choice with initial endowments, ability and tastes ($p+a$). Ability as one component of $p+a$ generates positive sorting into school attainment; the more able, the higher school attainment. However, the joint presence of taste of schooling makes this "ability sorting" incomplete. In other words, the tastes of individuals work as friction to sorting. Only individuals with the highest ability and taste will choose a college.

Since the standard deviation of ability is normalized to 1, the degree of sorting by ability into educational attainment is controlled by a single parameter, dispersion of tastes in each cohort, $\sigma_{p,\tau}$. As $\sigma_{p,\tau}$ falls, less variation in $p + a$ comes from variation in p and more from variation in a. In this case, workers are more sorted by ability across school groups, meaning ability gaps are more significant. In this case, the quantitative role of mean ability in explaining observed wage patterns across school groups will be larger.

First result: The recent college graduates cohorts are more able than the previous ones

Hendricks and Schoellman (2014) find that the calibrated dispersion of tastes, $\sigma_{p,\tau}$, declined substantially between the 1910 and 1960 cohorts, indicating that ability played a much more significant role in determining who continued to college for the 1960 cohort. They document data showing that low-ability students are becoming less likely to attend college over time which is consistent with a relative increase in the dispersion of ability for schooling. In other words, those who graduate from college are more of both higher abilities and tastes to pursue college studies.

Second result: Increase in the college wage premium gap due to an increase in mean ability gap over the time

The authors use the first result and the specific features of the wage equation to explain the growing trend in the college wage premium over the past decade. The average wage of workers from cohort τ with education s at age ν is given by

$$\mathbb{E}\left[\ln y|s,\tau,\nu\right] = \underbrace{\theta\,\mathbb{E}\left[a|s,\tau\right]}_{\text{ability effect}} + \underbrace{z(s,\tau+\nu-1)}_{\text{skill price effect}} + \underbrace{h(s,\nu)}_{\substack{\text{human capital}\\ \text{effect}}} . \tag{21}$$

The right-hand side includes three components. The authors aim to separate the role of the first component (effective ability) in explaining wage patterns from the other two terms. The first result of the paper revealed that the difference in the average ability, $\mathbb{E}\left[a|s,\tau\right]$, between college and high school graduates is increased over time. The authors also find higher θ for college students, which determines the higher impact of the average ability on the average wage. The authors find that the increase in the college wage premium since 1950 can be attributed to the expanding gap in mean ability between college and high school graduates.

1.7.2 Reversal in the college attendance predictor after World War II

Hendricks et al. (2021) extend the study made by Hendricks and Schoellman (2014) that documents the increasing role of student abilities for college entry over the twentieth century. They provide a quantitative theory of these changes: rising demand for college and the introduction of standardized test scores generated the increasing college stratification, which made college more attractive to high-ability students but less appealing to low-ability students.

The authors collect and harmonize 40 historical studies documenting college entry rates by student abilities and family background. They focus on the college attendance rates for two high school graduation cohorts, 1933 and 1960.[56] They estimate the impact of family characteristics on college enrollment conditional on academic ability. The authors find that

[56] The analysis of this paper stops in 1960 mainly because the federal government expanded college grant and loan programs after this time. These programs had significant effects on cohorts after 1960.

after World War II, the role of family financial background declined. At the same time, the role of academic ability rose, named as a reversal in college entry patterns.

The authors propose a theory for these changes based on three pieces of evidence: the significant increase in college enrollment after World War II, exercising selective admissions based on standardized testing such as SAT (Scholastic Assessment Test) and ACT (American College Testing).[57,58] Ultimately, the increased demand for colleges, coupled with the integration of standardized test scores, leads to a stratification of colleges into high- and low-quality institutions. This shift attracts students with higher abilities, particularly in higher-ranking colleges.

The model

The model economy contains a discrete number of locations (islands) indexed by $i \leq I$. There exists a single college and a measure of 1 of new high school graduates per year in each location.

Colleges are heterogeneous in their quality, q_i, that depends on both their endowments (the land, buildings, and financial resources), $\bar{q}_i$, and the mean ability of their students, $\bar{a}_i$, $q_i = \bar{q}_i + \bar{a}_i$.[59] Colleges set their own admissions policies that specify the expected ability of prospective students. Ability is not observable to colleges and students when application and admissions decisions are made. Instead, they form expectations about the student's ability.

Colleges set an admissions criterion, $\underline{a}_i$, specified as a minimum expected ability for acceptance. The college objective is lexicographic, meaning their priority is to maximize enrollment, e_i, until it hits capacity, E.[60] For colleges at capacity, their goal is to maximize quality, which leads them to set the highest value of a_i that maintains full enrollment.

[57]The authors take this increase in college demand as given and mention that the exact source of the rise in demand for college is not essential for their results.

[58]SAT is a paper-based entrance exam used by most colleges and universities in the United States to make admissions decisions. ACT is a paper-based and computer-based standardized admissions test primarily used by US and Canadian universities or colleges.

[59]q_i is uniformly distributed on the interval $[\underline{q}, \bar{q}]$.

[60]High enrollment is critical for colleges because they need to finance enormous fixed costs associated with the maintenance of their buildings.

High school graduates have heterogeneous endowments (a, f, z, s, ℓ).[61] Where a is their schooling ability and two noisy signals, s and z. s represents the information provided by scores on standardized college admissions tests, which are available only to postwar cohorts. z represents the information available without test scores in a student's transcript (courses taken, grades, rank in class) and letters of recommendation. f is the family background, and ℓ is their endowed location, which determines the quality of their local college.[62] Cohort t students form the expected ability based on their information set, $\mathbb{E}(a|\mathcal{I}_t)$.[63] The prewar information set, $\mathcal{I}_t = (f, z)$ is different than that of postwar cohorts, $\mathcal{I}_t = (f, z, s)$.

Students decide whether to attend the local college, attend college elsewhere, or join the labour market right after high school. Their decisions are irreversible. High school graduates who enter the labour market obtain a continuation value of V_t^{HS}. If they continue studies, upon graduation, they acquire human capital given by $h(a, q) = [\phi q^\gamma + (1-\phi)a^\gamma]^{\alpha/\gamma}$, where the parameter ϕ is the weight on quality in the production of human capital, γ governs the elasticity of substitution between ability, a, and quality, q, and α is the overall curvature of human capital formation. If the student's expected ability exceeds the local college's cutoff, $E(a|\mathcal{I}_t) \geq \underline{a}_\ell$, then attending the local college will be feasible, and it's total value is given by

$$V(f, \mathcal{I}_t, \ell) = \underbrace{\ln f}_{\substack{\text{consumption flow utility} \\ \text{while in college}}} + \overbrace{\alpha\, \mathbb{E}_a \left[\underbrace{\ln \left([\phi q_\ell^\gamma + (1-\phi)a^\gamma]^{1/\gamma} \right) |\mathcal{I}_t}_{\substack{\text{future consumption} \\ \text{proportional to human capital}}} \right] + V_t^C}^{\text{continuation value}},$$

where V_t^C is the relative value of attending college.[64] The total value of attending the "non-local college" is given by

$$W(f, \mathcal{I}_t, \ell) = \mathbb{E}_{a,\zeta_i} \left\{ \max_{i \neq \ell : \mathbb{E}(a|\mathcal{I}_t) \geq \underline{a}_i} V(f - \kappa, \mathcal{I}_t, i) + \bar{\zeta}\zeta_i \right\}.$$

[61] Endowments are drawn from a distribution $F(a, f, z, s)$ that is constant across locations and over time.

[62] Family background can be thought of as including transfers from parents plus income from work while in college, minus tuition payments.

[63] Ability is unobservable to students and colleges when application and admissions decisions are made.

[64] Both V_t^C and V_t^{HS} vary over time to capture changing wages and the non-pecuniary aspects of working as a college or high school graduate, respectively.

Students can attend any college out of their islands where their expected ability meets the admissions criteria, $E(a|\mathcal{I}_t) \geq \underline{a}_i$. However, applying to non-local (out-of-state) colleges is expensive for students from low-income families because they need to pay a financial cost of κ, which represents transportation costs, application costs, out-of-state tuition fees, and so on. ζ_i is an $i.i.d.$ type-I extreme value taste shock for college i. The parameter $\bar{\zeta}$ controls the dispersion of the shocks. Students choose among three options to maximize their lifetime utility (work as a high school graduate, attend the local college, search among all colleges and attend out-of-state colleges)

$$\max\left\{V_t^{HS} + \bar{\eta}\eta_{HS}, V(f, \mathcal{I}_t, \ell) + \bar{\eta}\eta_V, W(f, \mathcal{I}_t, \ell) + \bar{\eta}\eta_W\right\}, \tag{22}$$

where $\{\eta_{HS},\, \eta_V,\, \eta_W\}$ are $i.i.d.$ type-I extreme value taste shocks scaled by $\bar{\eta}$. The authors calibrate the model based on NLSY79 to show that it can generate a quantitatively significant reversal of who attends college; they simulate two equilibria of the model, corresponding to the equilibrium of the 1933 and 1960 cohorts. In a simulation, they vary V_t^C as the driving force to fit the fraction of each college cohort, representing the rise in college enrollment. Also, they vary $\mathcal{I}_t$, which captures the improved signals of students' abilities after the introduction of standardized testing.

Results

The model mimics the significant reversal in college attendance patterns in the United States. Before World War II, family income and socioeconomic status were more significant predictors of college attendance, whereas academic ability was more critical afterward.

Remarks

As mentioned by the authors, in this model, agents do not borrow from any source (such as taking a governmental loan). Also, the calibration is done using NLSY79 and not the later datasets, such as NLSY97. As stated by the authors: "the reversal in sorting patterns appears to be complete by this time (1960), with Belley and Lochner (2007) showing that the trend even reversed for later cohorts." (p.213). In other words, parental income may be essential for the later cohorts after 1960.

1.7.3 A historical puzzle

In their study, Castro and Coen-Pirani (2016) explore the developmental trajectory of educational attainment among birth cohorts of U.S. white males panning from 1932 to 1972. The research harnesses data from the 1950 and 1960 U.S. Census and the 1964-2010 March Current Population Survey (CPS). The central aim of the authors is to discern the contributing factors that elucidate the varying educational achievement levels observed across distinct cohorts.

A puzzle

The authors provide an elucidation for a perplexing phenomenon evident in the data. Specifically, certain periods within the data exhibit substantial increases in college premiums. However, the corresponding trend in college attainment does not align with this pattern, resulting in an intriguing paradox: *a heightened college wage premium coinciding with a diminished college completion rate.*

Figure 1.1 depicts that the earnings premium of a college degree relative to high school significantly increased after 1980. In the meantime, Figure 1.2 shows that college attainment increased after 1980 (for cohorts after 1960), but these increments were not at the same pace as the earning premium.[65]

Also, data show a higher growth of college attainment for cohorts before 1950, when the earnings premium was not growing enough to justify this drastic supply of college graduates at that time, shading a doubt on the earnings premium as the primary driving force for college attainment.

[65]Four possible levels of education are based on the highest completed grade: (1) more than ninth and less than twelfth grade is *high school dropout* (2) twelfth grade or a high school degree is *high school graduates* (3) less than four-year college is *some college* (4) at least a four-year college degree is *college graduate.*

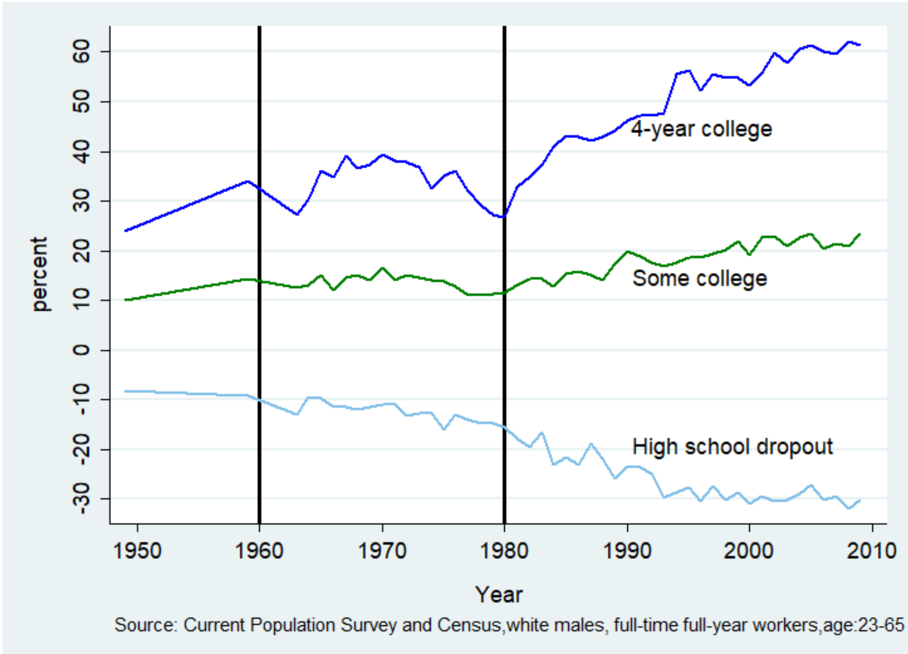

Figure 1.1: Earnings premiums relative to high school degree

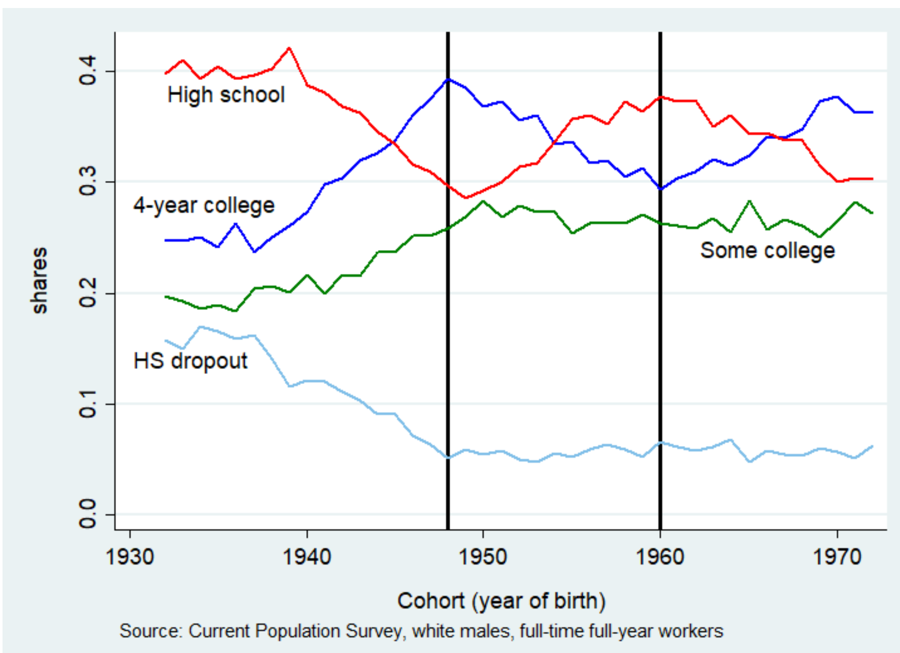

Figure 1.2: Educational attainment by birth cohort

The model is thoroughly explained in the supplementary appendix titled Appendix B.8. Castro and Coen-Pirani (2016) conclude that other factors also play a role in educational attainment evolution in the U.S. The authors quantify the contribution of all possible factors to the early rise (1932–1948 cohorts) and subsequent trends in college attainments. These factors are time-varying skill prices, variations in college tuition and fees, education quality (expenditures per student) and, more importantly, the learning ability and taste of individuals in various levels of schooling.

Findings

The authors find different results by turning off all of the model's driving forces and turning them on sequentially. They find that rising relative skill prices for college graduates in the 1950s and 1960s account for most of the increase in college graduation rates of the 1932–1948 cohorts. They also find that the subsequent decline in college attainment is due to rising tuition and declining average learning ability. Moreover, the learning ability channel is the *single-most important factor* in accounting for the observed decline in college graduation rates of the 1948–1960 cohorts. Most importantly, this paper's results suggest that declining average learning ability explains the puzzle for the college attainment of cohorts 1960 onward: the less steep trend of college completion rate compared to that of a college wage premium for cohorts 1960 onwards.

1.8 Determinants of college or college major choices

A long literature in various disciplines, such as sociology and psychology along with economics, examines the determinants of the choice of college study or the choice of college major.[66] In economics, the main dominant factors affecting students' choices can be expected labour market outcomes, perceived ability or skill endowments, and taste related to the field of study or the occupation (preference, enjoyment, interests).

The economic models either use observed choices and earnings data and rely on the

[66]The relevant studies in disciplines other than economics have tried to answer questions such as how social structures and external forces shape sorting into majors or how personality traits are related to college major choices (Coenen, Borghans, & Diris, 2021, , as a recent example in psychology).

rational expectations assumption to identify model parameters or count on students' beliefs elicited directly by the experimental approach. In this section, I categorize the main determinants from the existing literature in economics, including both strands of rational and non-rational expectations approaches.

Pecuniary factors

Economists have long been interested in knowing whether expectations about future life cycle earnings influence school or occupational choice (this literature includes, but is not limited to Abramitzky, Lavy, & Segev, 2019; Altonji, 1993; Arcidiacono et al., 2012; Attanasio & Kaufmann, 2014, 2017; Berger, 1988; Boudarbat, 2008; Han & Winters, 2020; Hurwitz & Smith, 2018; Long, Goldhaber, & Huntington-Klein, 2015; Montmarquette et al., 2002). Some of these studies and their approaches are already discussed in the previous sections.

it is also worth mentioning the early work by Berger (1988), who focuses on the influence of expected earnings streams. He follows the idea of Willis and Rosen (1979), who suggest that the present value of predicted future earnings streams is essential for deciding whether to attend college. The authors aim to show that individuals are forward-looking when choosing college majors. Contrary to myopic agents, forward-looking agents consider the future consequences of current actions. More specifically, the author shows that students are more influenced by their long-run earnings prospects and the expected flow of future earnings, not just the starting salaries; individuals are not myopic.[67]

Berger (1988) applies a life cycle approach to college major choice and assumes that individuals are certain about college completion and choose a field of study that maximizes their lifetime utility

$$V_{ij} = \alpha Y_{ij} + Z_i \gamma_j + \varepsilon_{ij}, \tag{23}$$

where V_{ij} represents the utility for person i in major j. Y_{ij} is the individual i's prediction of future earnings in major j. The Z vector consists of individual-specific variables controlling

[67] Examples of scholars who assume that expectations are myopic are Freeman (1971, 1975, 1976); Siow (1984); Zarkin (1985); Hoffman and Low (1983).

for taste and investment cost differences. Individual i chooses major j if $V_{ij} > V_{ik}$ for all $k \neq j$. Using the National Longitudinal Survey of Young Men (NLS) data, the author estimates wage equations for several majors with corrections for selectivity bias based on a reduced-form conditional logit model of major choice.[68]

The author finds that the imputed lifetime earnings measures correlate with undergraduate major decisions. More specifically, he shows that the higher the present value of the expected earnings stream from a terminal undergraduate degree in a particular major, the greater the likelihood of selecting it.

Non-pecuniary factors

A part of the literature on the determinants of college or college major choices emphasizes non-pecuniary aspects of individuals' utility as the primary determinant for college or major choices (with expected earnings playing a minor role). I divide this literature into the following main categories, and most of them are explained in the previous sections of this dissertation.

Taste or preference

Some literature focuses on perceived enjoyment (taste or preference) as the main drive for educational attainments. This literature includes (but is not limited to) Beffy, Fougère, and Maurel (2012); Zafar (2013); Gemici and Wiswall (2014); Wiswall and Zafar (2015a); Baker et al. (2018); Patnaik, Venator, et al. (2020); Wiswall and Zafar (2018, 2021); Arcidiacono et al. (2020); and Belzil and Hansen (2020).

Ability / skills

Some other literature focuses on ability (preparedness) as the most important determinant in college investment. This literature includes (but is not limited to) Keane and Wolpin (1997); Keane and Wolpin (2000); Belzil and Hansen (2003); Arcidiacono (2004, 2005); Stange (2012); Stinebrickner and Stinebrickner (2012, 2014a, 2014b); Giustinelli

[68]The number of majors in NLS was reduced to five distinct fields: business, liberal arts (humanities and social science), engineering, science, and education.

(2016); Arcidiacono, Aucejo, Maurel, and Ransom (2016); Belfield, Boneva, Rauh, and Shaw (2020); and Arcidiacono et al. (2020).

Parental transfers and borrowing constraints

The role of family contributions in the college investment decision and borrowing constraints has been extensively studied.[69] Borrowing constraints, similar to taste, are considered friction to ability sorting, which may hinder high-ability students from enrolling in or graduating from postsecondary institutions. However, borrowing constraints differ from tastes. Tastes are symmetric; they may prevent high- and low-ability students from pursuing college studies. However, borrowing constraints are asymmetric; they prevent some high-ability students from furthering their education but do not affect low-ability students (Hendricks & Schoellman, 2014). To what extent borrowing constraints could prevent students from furthering their studies is a debate in the educational literature.

On the one hand, some scholars who investigated the effects of borrowing constraints on schooling decisions present evidence suggesting that borrowing constraints have virtually no (or little) impact on schooling decisions. Examples are: Heckman et al. (1998); Cameron and Heckman (1998, 2001); Keane and Wolpin (2001); Sauer (2004); Cameron and Taber (2004); Nielsen, Sørensen, and Taber (2010); Johnson (2013); and Belzil and Hansen (2020). Also, Stinebrickner and Stinebrickner (2008b) finds no effect of credit constraints in explaining dropout behaviour.

On the other hand, some other researchers find that family income and credit constraints are fundamental to shaping college attainments (see, for example, Attanasio & Kaufmann, 2009; Bailey & Dynarski, 2011; Belley & Lochner, 2007; Chetty, Hendren, Kline, Saez, & Turner, 2014; Lochner & Monge-Naranjo, 2011).

Belley and Lochner (2007) underscores that a considerable portion of arguments against the significance of credit constraints are rooted in the analysis of the NLSY79 dataset. Nonetheless, numerous transformations have unfolded since that era, encompassing marked

[69] Keane and Wolpin (2001) defines borrowing constraints as restrictions on the availability of uncollateralized loans.

tuition increases, reductions in Pell Grant disbursements, and imposed caps on federal student loans. These shifts compelled younger generations to rely more heavily on borrowing to finance their college education, exerting amplified strain on families with limited financial means. Consequently, the constraints surrounding borrowing might exert a more pronounced influence on today's youth than the circumstances prevailing in the early 1980s.

The authors use data from the late 1990s and early 2000s (NLSY97) to investigate the abovementioned hypothesis. Their findings suggest that family income has become much more strongly correlated with college attendance for recent cohorts. In other words, credit constraint is vital in determining college attendance over time.

Using subjective expectation data from a household survey on Mexican junior and senior high school graduates, Attanasio and Kaufmann (2009) analyze the link between people's "subjective" expectations of returns to schooling and their decision to invest in education. They argue that credit constraints would break the link between expected returns (or risk perceptions) and schooling decisions. Their results highlight the critical role of credit constraints in college attendance decisions in Mexico.

Using both datasets of NLSY79 and NLSY97, Lochner and Monge-Naranjo (2011) develop a human capital model with borrowing constraints derived from government student loan (GSL) programs and private lending under limited commitment. They find that the credit constraint became tightened over time. Their model predicts that recent students' family resources have become a more important determinant of higher education.

Bailey and Dynarski (2011) use nearly seventy years of data from the U.S. Census, NLSY79, and NLSY97 to document changes in inequality in educational attainment by family income over time. They focus, in particular, on the thirty years since 1980. They find growing income gaps in college entry, persistence, and completion, for which they find increasing advantages for children growing up in high-income families.

However, they find that women primarily drive these increases in educational inequality. For example, the gap between the top and bottom quartiles in college entry increased by fifteen percentage points among women and seven percentage points among men. The authors mention three candidate explanations for increases in educational attainment inequality: widening inequality in parental income, changes in school quality and organization, and rising tuition prices.

1.9 Policy changes

In economics theory, financial programs increase students' disposable income and produce an income effect that enables recipients to pay for college costs and may induce them to reduce the time they allocate to work during college and increase their time to study. However, the pure income effect does not necessarily incentivize all students to significantly tilt their expenditures towards education as they also value the consumption of goods and leisure (Garriga & Keightley, 2013).

There is a broad literature using either structural analyses or quasi-experimental methods studying the impacts of a policy change on schooling and labour market outcomes.[70] In this section, I briefly review the educational policy literature to affect educational outcomes such as college enrollment and completion rates. Many scholars estimate the causal impact of schooling costs and financial assistance such as loans, scholarships and grants on schooling decisions. Their estimates mostly deliver positive results of aid and loans for four-year college enrollment. These policies align with those I will implement through simulations of my economic model in Chapter 3.

1. Increase in limits of merit-based scholarships

Since 1991, several states have applied merit-based aid programs to alleviate the higher education costs among residents who meet specific academic criteria. Many studies investigating these state-sponsored programs show significant positive effects of merit-based grants on college enrollment.

[70] Quasi-experimental studies investigate the effects of changes or differences in tuition or aid level before and after a specific time.

Dynarski (2000) uses the Georgia HOPE Scholarship, a state merit-based aid program, in estimating the effect of schooling costs on college attendance.[71] Based on data from the 1989–97 October Current Population Surveys (CPS), she uses a difference-in-differences (DID) methodology before/after the institution of the HOPE scholarship in 1993. Using a set of nearby states as a control group, she finds that for each $1,000 (in 1998 dollars) of grant aid, the college attendance rate rises by 3.7 to 4.2 percentage points. In a similar study, Cornwell, Mustard, and Sridhar (2006) finds that the HOPE program raised the total first-time freshmen enrollment in Georgia colleges by around 6%.

Kane (2003) uses a regression discontinuity design and studies the impact of the Cal Grant program in California on college-going. He concludes that receiving the Cal Grant Award raises college enrollment by 3 and 4 percentage points. Also, Bettinger, Gurantz, Kawano, Sacerdote, and Stevens (2019) examine the long-term impacts of the Cal Grant program. They find that the Cal Grant financial aid significantly increases the probability of earning a bachelor's degree by 3 to 4.6 percentage points.[72]

In a recent study, Castillo, Collins, and Maynard (2020) review the impacts of six state "Promise" programs providing no-cost tuition for in-state students at public community colleges.[73] In this study, the authors find substantial increases in enrollments by low-income

[71] In 1993, Georgia introduced the Georgia HOPE (Helping Outstanding Pupils Educationally) Scholarship. The program allows free attendance at Georgia's public colleges for state residents with at least a B average in high school.

[72] California's Cal Grant program is one of the most extensive and generous state-based financial aid programs. This program is administered by the California Student Aid Commission (CSAC). Grants are for students attending the University of California (UC), California State University (CSU), California Community College or qualifying independent and career colleges or technical schools in California. Eligibility requires students to meet minimum thresholds on three characteristics: income, assets and a minimum high school Grade Point Average. Source: California Student Aid Commission, (last accessed December 2023).

[73] Following "free college" policies, sixteen states in the U.S. currently have active locally-based "Promise" (Providing Real Opportunities to Maximize In-state Student Excellence) programs. These State aid merit-based programs began in 2005 with the announcement of the Kalamazoo Promise, which offers full in-state college tuition to graduates of the Kalamazoo Public Schools in Michigan who had been enrolled in the district for at least four years. Most Promise programs offer free education at community colleges but not four-year institutions. The Tennessee "Promise," funded by Tennessee, is a novel tuition assistance program within the two-year college sector. Starting from the 2015-16 academic year, Tennessee residents/U.S. citizens/eligible non-citizens/students who graduate from an eligible high school, home-school, or earn a GED/HISET (before their 19th birthday) can receive an award at an eligible postsecondary institution toward tuition and mandatory fees after all other gift aid has been first applied. Sources: Promise Programs, Tennessee Promise Scholarship, and The Future of Statewide College Promise Programs, (last accessed December 2023).

and minority students.[74]

Using a quasi-experimental method, Nguyen (2020) examines the effects of the Tennessee "Promise", a statewide free community college program, on eligible community colleges. The author identifies differences in program effects on enrollment across gender and racial/ethnic classifications. He estimates a 40% increase in registrations at eligible community colleges. Moreover, the author found significant increases for Black and Hispanic students.

Scott-Clayton (2011) examines the impact of the West Virginia "Promise" scholarship on bachelor's attainments in graduation rates and time-to-degree.[75] This scholarship is similar to other state merit programs in its initial eligibility requirements and the amount of aid offered. But it is unique in requiring students to complete 30 credit hours in 12 months if they receive a two-semester award to keep their scholarships.[76] Using a differences-in-differences regression discontinuity method, the author finds that "Promise" increased the overall Bachelor attainment rate by 1.8 to 2.3 percentage points.

2. Increase in limits of need-based grants

Many scholars investigated the effect of an increase in the need-based grant on college enrollment. Dynarski (2003a) uses a discrete shift in aid policy as a source of exogenous variation in aid. She uses a difference-in-differences methodology and examines the 1983 termination of tuition benefits for Social Security survivors. It was a program that provided generous stipends to children of deceased parents aged 18 to 22 who were enrolled full-time in college. Using the death of a parent during a person's childhood to proxy for Social Security beneficiary status, she finds that eliminating the Social Security student benefit program reduced college attendance probabilities by more than a third. These estimates suggest that an offer of $1,000 (in 2000 dollars) in grant aid increases the likelihood of college enrollment

[74] This review is intended as a complement to a previous systematic review of a subset of promise programs, Promises Fulfilled? A Systematic Review of the Impacts of Promise Programs, (last accessed December 2023).

[75] See: West Virginia Promise scholarship, (last accessed December 2023).

[76] Recently, some in-state students have been having problems with the scholarship's requirements of completing 30 credits per year. Advisors have told students that the conditions have changed, and 12 credit hours each semester must be "degree-pursuant." Source: WVU's Independent Student Newspaper (Mar 24, 2021), (last accessed December 2023).

by about 3.6 percentage points.

In another research, using a regression discontinuity methodology, Castleman and Long (2016) examine the effects of the Florida Student Access Grant (FSAG) on four-year college attendance, credit accumulation and bachelor's degree completion.[77] They find that FSAG eligibility positively impacts college enrollment and degree attainment. The additional $1,300 in grant aid eligibility (in 2000 dollars) increased the probability of immediate enrollment at a public four-year university by 3.2 percentage points.

Also, Castleman, Long, and Mabel (2018) investigate the effect of need-based grant eligibility on credit and degree attainment in STEM fields. Exploiting a regression discontinuity design, they find evidence that the FSAG award increased bachelor's degree attainment in STEM fields by three percentage points.

Furthermore, Denning, Marx, and Turner (2019), estimate the effects of the Pell Grant for low-income students. The authors use the student-level administrative data from Texas and a fuzzy regression discontinuity design. They show that additional grant aid affects the enrollment decisions of individuals on the margin of attending a community college by 3 to 9 percent.

3. Decrease in tuition and fees

Some studies investigate the effects of tuition assistance programs on college enrollment in the literature. Most find these programs increase college enrolment, especially for low-income and minority students. However, they do not investigate these effects separately on college majors such as STEM and ARTS.

Keane and Wolpin (1997) simulate the effect of an experiment that provides a $2,000 (in 1987 dollars) tuition subsidy for each year of college attendance. The authors report an increase in the proportion of graduating from college by 8.4 percentage points. Since

[77] The Florida Student Assistance Grant (FSAG) Program is a need-based grant program available to degree-seeking, resident, and undergraduate students who demonstrate substantial financial need and are enrolled in participating postsecondary institutions. Source: Florida Student Assistance Grant Program, (last accessed December 2023).

the model agents are forward-looking, a rise of 3.5 percentage points in the high school graduation rate (without attending college) also exists.

Using the difference-in-differences method, Abraham and Clark (2006) and Kane (2007) evaluate the District of Columbia Tuition Assistance Grant (DCTAG) program.[78] They examine the effect of the DCTAG program on the college application and enrollment decisions of D.C. residents. Abraham and Clark (2006) estimate an impact on college enrollment of 3.6 percentage points per $1000 (in 2000 dollars) of effective tuition reduction. Kane (2007) finds that the DCTAG program increased enrollment in D.C., and a $1,000 (in 2002 dollars) decrease in tuition is associated with a 5 to 6 percentage points increase in enrollment.

4. Increase in student loan limit

Compared to the studies on merit-based and need-based grants and tuition subsidies, relatively little research has investigated the effects of student loans on college enrollment or completion. Reyes (1995) examines the effect of relative changes in Guaranteed Student Loan (GSL) eligibility across income groups in the early eighties. She concludes that loan access increases attendance and completed schooling. More specifically, results show that college enrollment rates dropped three percentage points by losing eligibility for GSL in 1981.

Another study, using CPS and the 1990 Panel of the Survey of Income and Program Participation (SIPP), Dynarski (2003b) also investigates the changes in loan policy induced by the Higher Education Amendments of 1992, which removed home equity from the set of assets "taxed" by the federal aid formula. She finds a small effect of loan eligibility on college enrollment.

Developing a heterogeneous life cycle model, however, Ionescu and Simpson (2010) find that increasing government loan borrowing limits (from $23,000 to $31,000, an increase of around 35%) leads to a five percentage point increase in four-year college enrollment rates. This increase is almost for every student, and the largest increases occur for the poorest

[78]The District of Columbia Tuition Assistance Grant program established in 1999, allows D.C. residents to attend public colleges throughout the country at considerably lower "in-state" tuition rates.

students with the most financial need.[79]

A recent study employs institution-year-level variation. Wiederspan (2016) estimates the impact of access to loan aid using variation in community colleges' decisions to participate in or opt out of the Stafford Federal Loan Program. The author evaluates the within-college differences in outcomes for Pell-eligible students before and after opting out of the loan program. The results show that student loans positively affect the number of credits students attempt in their first year. Also, the author finds that student loan borrowing increases the number of credits completed, degree completion, and transfer to a four-year institution. However, the results are not statistically significant.

[79]The Stafford loan limit for dependent undergraduates is $31,000 for up to five years of postsecondary education. The loan limits represent a higher percentage of net college costs for low-asset students than high-asset students. This limit on government loans has remained constant since 2008. The previous limit was $23,000 and remained constant from 1993 until 2008.

Chapter 2

Life Cycle and the U.S. Data Statistics

2.1 Introduction

To model college major choices in Chapter 3, it is crucial to establish several key facts that will serve as a foundation for calibrating the model. The primary objective of this chapter is to identify and utilize three specific sets of information from the Panel Study of Income Dynamics (PSID) for the subsequent chapter. These sets of information include income life cycle statistics (mean, mean/median, and Gini), wage parameters (the wage growth rates), and the parameters of the human capital accumulation function (the depreciation rates).

In the next chapter, I will utilize the information to map my model to data and incorporate the necessary elements for simulating an economy. To begin, I will use life cycle statistics to determine the parameters of the initial distribution within the simulated economy. Furthermore, wage growth and human capital depreciation rates will serve as crucial parameters within the model. These rates will enable the simulation to account for economic changes and trends over agents' life cycles, particularly concerning three distinct educational levels: STEM, ARTS, and no-college.

The PSID is a longitudinal study focusing on a diverse sample of U.S. individuals, including men, women, and children, as well as their respective family units. This study emphasizes the dynamic aspects of economic and demographic behaviour, providing a comprehensive understanding of individuals' lives over time. One of the main advantages of using the PSID is its ability to track individuals over multiple years, allowing for the unique identification of their educational category with high precision. This feature differentiates it from other datasets, such as the Current Population Survey (CPS) and the National Longitudinal Survey of Youth (NLSY).

While the PSID may have a smaller sample size than the CPS, it compensates by following the same households over extended periods. This longitudinal nature of the PSID enables researchers to observe changes and patterns within specific families and capture the long-term effects of various factors, including educational choices, on economic outcomes. Furthermore, the PSID offers a substantial advantage regarding broader coverage of different cohorts compared to the NLSY. This expanded coverage enhances the generalizability and applicability of the findings derived from the PSID data.

In the following section, I will provide a more detailed explanation of the PSID dataset. Then, section 2.3 will outline the critical PSID variables utilized in this chapter. The subsequent section, 2.4, will elaborate on the data sample selection process. In section 2.5, I will describe the methodology employed to extract the age profiles, real income statistics, wages, and human capital accumulation parameters. Finally, section 2.6 summarizes the chapter. Located at the end of this dissertation, Appendix A provides all occupation and field codes essential for the empirical analysis conducted within this study.

2.2 The PSID dataset

This section provides an overview of the Panel Study of Income Dynamics (PSID).[1] The PSID offers several key advantages as a panel dataset, with its long coverage period being its primary strength. It is the longest-running representative household panel for the United States, with data collection initiated in 1968. Over the years, the PSID has consistently interviewed individuals from families included in the initial samples, regardless of their living arrangements or household composition. Initially conducted on an annual basis, the survey shifted to a biennial schedule starting from 1997 onward. This extended period allows researchers to examine long-term trends, track changes, and analyze intergenerational dynamics within American households.

The genealogical design of the PSID is a distinctive characteristic that sets it apart. The initial sample of the PSID comprised over 18,000 individuals residing in approximately 4,800 families across the United States, all of whom were interviewed in the inaugural year of the survey, 1968. These individuals, called the "PSID gene," were considered permanent study members. As the original PSID family members form new households, these new families also become part of the survey. Consequently, when children from the original PSID families establish their own homes, their spouses are included in the study. This intergenerational approach ensures that the original families and their subsequent "split-offs" have been continuously tracked since 1968, providing researchers with valuable insights into the dynamics of family formation and evolution over time.

The PSID has consistently maintained low sample attrition rates, which has resulted in significant growth in the sample size in recent years. From 1968 to 2019, the PSID gathered information on approximately 82,500 individuals, covering up to 52 years of their lives. This comprehensive dataset offers a wealth of information on both families and individuals. It includes extensive data on socio-economic characteristics, labour market experiences, income, wealth, education, health status, family structure, marriage, childbearing, child

[1]Main sources used for this section are Hill (1992), PSID Main Interview User Manual: Release 2021, and The PSID website (last accessed December 2023).

development, philanthropy, and more. Scholars, policy analysts, and graduate students worldwide continuously utilize this dataset, resulting in approximately 6,800 peer-reviewed publications relying on the PSID data.

Additionally, numerous countries have established studies similar to PSID to facilitate cross-country comparative research. Some notable examples include the German Socio-Economic Panel (SOEP), the British Household Panel Survey (BHPS), and Understanding Society: the UK Household Longitudinal Study (UKHLS). These initiatives commenced by conducting interviews with a selected group of households from the entire population of a particular country at a specific point in time. Subsequently, these same household members (and their descendants) were interviewed regularly.[2,3,4]

In summary, the extensive panel, comprehensive genealogical structure, and diverse content of the PSID data make it an excellent data source for investigating various aspects of household behaviours. The significance of the PSID is underscored by its recognition as one of the 60 most notable advancements funded by the National Science Foundation (NSF) in its 60-year history, with the NSF serving as the primary sponsor.

SRC and SEO sub-samples

The original sample comprised two primary sub-samples: the Census Bureau's Survey Research Center (SRC) and the Survey of Economic Opportunity (SEO). The SRC sub-sample was intended to be an equal probability sample of 3,000 families residing in the continental US, and it was selected by the University of Michigan's Survey Research Center. However, due to non-participation by certain families, only 2,930 interviews were completed out of the initially targeted 3,000 families.

[2] The German Socio-Economic Panel (SOEP) is a longitudinal survey of approximately 11,000 private households in the Federal Republic of Germany from 1984 to 2019 and the eastern German länder from 1990 to 2019 (release 2021). See more in Research Data Center SOEP (last accessed December 2023).

[3] BHPS data are available through the UK Data Service for researchers who demonstrate that their work is in the public interest (last accessed December 2023).

[4] Understanding Society, the UK Household Longitudinal Study (UKHLS), is one of the most extensive panel surveys globally, supporting social and economic research. Its sample size is 40,000 households from the United Kingdom or approximately 100,000 individuals. See the UK Household Longitudinal Study for more information (last accessed December 2023).

The SEO sample was designed to include 2,000 low-income families selected from the U.S. Census Bureau's Survey of Economic Opportunity. However, only 1,872 families participated in the first PSID interview. The SEO sample targeted individuals residing in Standard Metropolitan Statistical Areas (SMSAs) and non-SMSAs in the southern region. The SRC/SEO composite sample is a probability sample characterized by an uneven probability of selection. Sample weights have been incorporated for adjustment purposes to ensure that descriptive statistics accurately reflect the population.

2.3 Definitions of key variables

A detailed definition of the key variables used in this dissertation and the relevant modifications follows.

Income. Head's labour income variable is the total income derived from labour, excluding revenue from farm-related activities and unincorporated business ventures. This variable encompasses various components of labour income, which are derived from the raw data. In addition to regular wages and salaries, it includes separate reports of bonuses, overtime pay, tips, commissions, income from professional practices or trades, additional job income, and miscellaneous labour income sources such as market gardening and income from the accommodation as roomers and boarders.

In the next chapter, the *Income* variable will be utilized to compare the labour income of agents in the model and calibrate the initial distribution of the model economy. However, it is essential to note that this variable excludes revenue from self-employment, such as self-employed farmers and unincorporated businesses. The exclusion of self-employment revenue is necessary since only the market labour component of income is relevant for calibrating the model parameters in the upcoming chapter.

In the PSID, the question regarding this particular variable is retrospective, meaning the variable recorded in the survey year t corresponds to the calendar year $(t-1)$. To account for the timing discrepancy, I apply a shifting process to the values of this variable, aligning them with the previous years. By doing so, I am effectively adjusting the income variable to ensure consistency and accuracy.

Hours. The variable "Head's annual hours of work" represents the total number of hours worked by the head of the household in a year, including overtime. It is calculated retrospectively by the PSID based on the information provided on the usual hours worked per week and the number of actual weeks worked in the last year. The values for this variable reflect the annual hours worked for monetary compensation on all jobs, including any overtime worked.

Wage. An available measure of hourly wage in the PSID provides the current hourly wage at the time of the interview. However, it is essential to note that this measure is only sometimes available throughout the entire study period. Additionally, it is worth mentioning that there have been some errors in data entry for this measure. To address these limitations, I use the alternative approach of calculating the wage by dividing the annual labour income by the annual hours worked. This method of computing wages has been employed in previous studies such as Heathcote, Storesletten, and Violante (2014) and Abraham and Clark (2006).

Education. This variable, referred to as the survey year, is not retrospective. In the context of the PSID, specific codes are provided for different levels of education, allowing me to limit the sample to individuals who have obtained either a high school degree or a college degree. I have excluded individuals with less than a high school education, some college education, and graduate studies because the model presented in Chapter 3 does not cover these categories. These excluded categories account for approximately half of the initial sample, approximately 79,000 observations.

Occupation of Head. The PSID collects information regarding the occupation of the Head working for the primary employer. To categorize occupations consistently over time, the PSID relies on three Census Code documents provided by the U.S. Census Bureau. These documents include three-digit occupation codes from the 1970 Cencus used for the years 1968-2001, three-digit occupation codes from the 2000 Cencus used for 2003-2015, and four-digit occupation codes from the 2010 Cencus used for 2017-2019. These codes provide a standardized system for classifying occupations, enabling the PSID to track changes and trends in employment patterns over time. All these occupational codes are provided in Appendix A.

Additionally, the PSID utilized one- and two-digit occupation codes in specific survey years before 1980. However, it is worth noting that three- and four-digit codes offer more extensive occupations, providing greater granularity than their one- or two-digit counterparts. By employing three- and four-digit codes, a more detailed understanding of the human capital within the two interest categories, STEM and ART, can be attained. The occupational titles associated with these categories are more likely to be specific to the three- and four-digit classifications rather than the broader one- or two-digit classifications. Hence, for the identification of STEM and ARTS categories, I will rely on the three- and four-digit classifications derived from 1970, 2000, and 2010 Census of Population.[5]

The PSID plays a crucial role in this paper by providing compatible occupation codes as proxies for college degrees. These occupation codes enable me to examine how the real income of three specific educational groups - “college STEM,” “college ARTS,” and “no-college path” - changes over time and with age. Nevertheless, there is a need for more accurately identifying college majors using these occupational codes. Individuals can graduate in a particular major but work in occupations not specific to their field. To address this potential misclassification, I have developed a technique called "fine-tuning" that allows me to retrieve individuals’ majors during the years they worked in occupations unrelated to their major-specific fields. In the following section, I will provide a detailed explanation of this fine-tuning technique.

[5]This strategy is similar to that of Kambourov and Manovskii (2009) by utilizing three-digit codes from the 1970 and 2000 Census.

2.4 Sample selection

The empirical analysis relies on the 1968 core sample (SRC and SEO) with positive sampling weights to ensure consistent sample representativeness over time. To maintain the sample's representativeness of the U.S. population in each period, I employ the PSID longitudinal family weights for sample weighting. Certain family heads with zero weight are excluded from the estimation in this process.

In this paper, two types of PSID datasets are utilized. The first type is the *single-year family files*, which consist of a single record for each family interviewed in a particular year. The second type is the *cross-year individual files*, which provide individual-level data. Both data files include the identification number (ID) of the family with whom the person is associated each year. By leveraging the family ID and sequence number variables, I perform a matching process to merge the two sets of PSID data. This experiment created a panel dataset encompassing individuals' relevant information across the survey years from 1968 to 2019.

To generate my sample, I focus on male heads of households aged 25-59. Following the approach employed by Huggett et al. (2006), I use a terminal age set earlier than the conventional retirement age. This decision to select a relatively lower terminal age is motivated by two primary factors. Firstly, the PSID dataset I utilize needs sufficient observations toward the end of the working life cycle. Therefore, setting a higher terminal age would result in a diminished sample size and potentially compromise the robustness of the analysis. Secondly, there is a notable decline in labour force participation as individuals approach the traditional retirement age. By choosing a lower terminal age, I can focus on a period of relatively stable labour force participation rates, ensuring that my sample remains representative of the intended population and minimizing potential biases associated with retirement-related transitions.

In the PSID, the primary level of detail is obtained for the primary adults in the family unit, specifically the Head. The decision to primarily focus on male heads is based on the fact that the issue of zero earnings is generally less prevalent among males than females. As a result, this approach allows for a more comprehensive analysis of income dynamics within the dataset. Additionally, specific observations within the dataset are excluded from the study. This includes cases where income values are zero, top-coded (i.e., limited to a maximum value), or missing. The analysis can focus on individuals with valid and meaningful income data by excluding these observations. Furthermore, I adjusted the income data in the PSID using the consumer price index (CPI) for all items, normalized to 100 in 2014. This adjustment ensures that income values are adjusted for inflation and presented in real terms.[6]

To focus specifically on heads of household and exclude other potential earners within a family unit, I have chosen to keep individuals currently working or temporarily laid off and exclude students, retirees, or self-employed. Additionally, I have implemented a filtering mechanism to remove improbable outliers at the lower end of the wage distribution. Following the approach described in Heathcote, Perri, and Violante (2010), I eliminate heads of household each year whose hourly wage falls below half the legal minimum for that particular year. Furthermore, taking inspiration from Blundell, Pistaferri, and Preston (2008), I exclude observations with annual wage growth exceeding 500 percent or falling below -80 percent to mitigate measurement errors.

Correction for age variable. Some individuals may have gaps or jump in their age variable, which can be attributed to typing errors made by interviewers. In the existing literature, two approaches have been proposed to rectify these errors in the age variable.

On one side, Hryshko (2012) proposes a method that utilizes an individual's age the first time they appear as a head in the survey to estimate their age in future years. Conversely, Blundell et al. (2008) suggests using an individual's age at the last time they appeared as a head in the survey to estimate their age in previous years. In my research, I opt for the latter approach because significant efforts have been made to clean the PSID data over time,

[6]I have chosen 2014 as the base year to establish parameters related to college costs, student loans, and tuition and fees for the five academic years, specifically from 2014-2015 through 2018-2019. These parameters will be utilized in the model economy presented in the upcoming chapter.

making recent data less prone to data entry errors by interviewers.

Correction for education variable. The PSID includes questions about education when there is a change in the family unit, such as acquiring a new head, spouse, or partner. In all other cases, the education variable is carried forward from previous years' data. However, there have been limited instances where education was reported in specific years, namely 1968, 1975, 1985, and 2009, for existing heads of households. Consequently, education is kept constant between these updating years. To illustrate, If an individual reported having 11 years of education in 1985 and 16 years in 2009, documenting their education level as 11 between 1985 and 2009 may introduce a bias toward a lower educational level within the dataset. To mitigate this issue, I use a more appropriate approach to fix the education variable equal to its mode value among all the available reports for 1986-1990 and 1991-2019. This adjustment accounts for the potential discrepancy and prevents them from being counted as less educated than in the broader period of 1990-2009. It minimizes the downward bias in reporting individuals' education levels in the sample.[7]

Linear interpolation. Exploiting the PSID data until the most recent waves are challenging due to the decrease in data frequency after 1996 (the survey year 1997), from annual to biennial. I employ an averaging technique to address the missing years in the PSID dataset (specifically 1998 and every two years up to 2018). I calculate the average values of the preceding year $(t-1)$ and the subsequent year $(t+1)$ for income, age, and hours variables. I also calculate and apply the average growth of each person's weight for the weight variable. This assumption allows me to estimate the missing values based on the data available in the adjacent years. Regarding other variables of interest, such as education, occupation, and employment status, I assume that the heads of families remain in the same situation as in the preceding year. Given the limited data available during the missing years, this assumption allows for a reasonable approximation of these variables.

Retrospective variables. Following the resolution of missing biannual years, I adjusted the sample by shifting the values of the retrospective variables (income and hours) back by

[7] In 1991, there was a change in the coding system of the PSID for the education variable.

one period.

Business and Finance, Law, and Sports categories. Before deciding between STEM and ARTS, I identified several categories and excluded them from consideration. Appendix A offers a comprehensive list of relevant occupation Census codes discussed in this paper.

STEM category. I selected the STEM and STEM-related codes from the occupational code lists of 1970 and 2000. These code lists were derived from the 2010 Census Code list, which provides occupational codes categorized into main desired categories such as STEM, ARTS, business and financial operations occupations, legal occupations, and more.[8,9] The Occupation Code List 2010 was developed by the Standard Occupational Classification Policy Committee (SOCPC) and subsequently authorized by the Office of Management and Budget (OMB). It was formulated using the Standard Occupational Classification (SOC) System 2010.

Using the Occupation Codes mentioned above helps to classify the categories of interest: STEM and ARTS. However, some limitations can result in the misclassification of individuals. For instance, there are cases where individuals may have graduated in STEM but currently work in ARTS, and vice versa. Additionally, certain occupations, such as supervising or management roles, may be shared across all categories of college graduates.

For example, if someone initially worked as an engineer for several years but later transitioned into a managerial position, they would still need to be assigned to the STEM category, even though management is not explicitly defined in the STEM list. This is especially important when conducting studies that track individuals throughout their entire working life cycle, as STEM individuals should always be treated as STEM regardless of their current occupation.

[8]Source: U.S. Census Bureau, Industry and Occupation Code Lists & Crosswalks. For the list of 1970, 2000 Occupational Census Codes and Categories, see 1970 Industry and Occupation Code List, and Census 2000 Occupational Classification System and Crosswalk to Standard Occupational Classification (SOC), respectively (last accessed December 2023).

[9]For the 2010 Code list, see "STEM, STEM-related, and Non-STEM Occupation Code List 2010" Excel file in Industry and Occupation Code Lists & Crosswalks (last accessed December 2023).

According to the Census Bureau's 2019 American Community Survey 1-year estimates, less than a third (28 percent) of individuals with STEM education are employed in a STEM occupation.[10] Various scholars have explored the problem of occupational mismatch for STEM graduates. Samantha and Andrew (2020) utilize restricted-level data from the Educational Longitudinal Survey of 2002 (ELS:2002) and demonstrate that over 25 percent of STEM baccalaureate graduates did not intend to remain in a STEM field by age 30. In a separate study, Kim, Jung, and Mlambo (2021) investigated the relationship between institutional selectivity and the likelihood of working in STEM jobs. They analyze data from the National Survey of Recent College Graduates and find that selective schools are more effective at retaining STEM graduates in STEM occupations than less selective ones.

This issue gains additional significance in light of the substantial increase in occupational mobility observed over the past three decades (Kambourov & Manovskii, 2009). This upward trend can be attributed to several factors, such as the hypothesis proposed by Jovanovic and Nyarko (1997) that many occupations act as stepping stones for career advancement into management positions. Additionally, the rise in mobility may be influenced by technological advances, globalization, international trade, shifts in government regulations, and the impact of labour force unionization ((Kambourov & Manovskii, 2009).

Fine-tuning of the STEM category. To create a more relevant and consistent selection process, I have implemented a "unifying" screening and selecting process immediately after defining the STEM category. Under this approach, if an individual has chosen to work in STEM occupations at any point in their life, they will be assigned to the STEM category for the entirety of their working years. This ensures that individuals who have worked in other non-STEM occupations, such as management (not specified as STEM in occupation Code Lists), are still kept within the STEM category as consistently as possible.

Another reason to implement the "unifying" screening and selecting processes is to address the limitations of the PSID, which utilizes the 1970 Census of Population occupation and industry codes consistently throughout the 1968–1997 periods. Certain professions

[10]Source: Does Majoring in STEM Lead to a STEM Job After Graduation?, (last accessed December 2023).

that emerged in the early 1990s may not have been included in the original 1970 Census classification. As a result, workers in these occupations may be erroneously coded as belonging to the “not elsewhere classified” occupational categories within the outdated classification system. By applying the “unifying” process to the STEM category, I can effectively capture and account for these occupations that may have been overlooked or classified incorrectly in the outdated system.

STEM related teaching occupation. The 1970 Code list includes specifications for STEM-related teachers, such as those in engineering, mathematics, or biology. However, the 2000 Census Code list does not provide specific STEM-related codes for teaching occupations. To address this issue, I categorize teachers in the dataset as STEM teachers if the PSID offers additional information about their “field” variable, such as indicating their specialization in engineering. In this regard, I used the “Field codes” provided in the dataset as the relevant codes for fields related to STEM and ARTS for more accurate categorization.[11]

ARTS category. For the ARTS category, I rely on the same Occupation Code Lists. However, it should be noted that no explicitly defined occupations were listed under the ARTS category in the 1970 and 2000 Occupation Code Lists. I refer to the 2010 Code list as a guide to determine the relevant occupations for this category. This list includes occupations such as Arts, Design, Education, Training, Library, Community and Social Services, Entertainment, and Media Occupations, which are considered relevant to the ARTS category.

Fine-tuning of the ARTS category. The same “unifying” process is applied to the ARTS category to ensure consistency. Similar to the approach used for the STEM category, individuals who have chosen to work in ARTS occupations at any point in their lives are assigned to the ARTS category for the entirety of their working years.

It is important to note that the fine-tuning technique must be done sequentially for STEM or ARTS. In this case, STEM fine-tuning is done first because the likelihood of a STEM person (with high ability) working in lower-skill jobs is higher than an ARTS person

[11] Appendix A also provides the relevant Field codes.

(with lower skills) working in higher-skill occupations. As a result, individuals who have worked in both STEM- and ARTS-related occupations are considered STEM individuals for categorization.

ARTS related teaching occupation. I selected specific categories from the 1970 Census, such as English and theology teachers, for teaching occupations in which the particular teaching topics are known. Additionally, teachers with an "unknown field of teaching" are placed in the ARTS category if they were not captured by any of the categories mentioned earlier, namely STEM, Business and Finance, Law, and Sport. Implementing the "unifying" process across these different categories and excluding them from the sample allows removing irrelevant teachers from the ARTS category.

The resulting sample consists of 63,108 person-year observations spanning the income periods from 1967 to 2018, with an average of 1,214 observations per year. Within this sample are 10,477 person-year data points for STEM graduates, 4,078 person-year data points for ARTS graduates, and 48,553 person-year data points for high school graduates.

2.5 Life cycle profiles and human capital parameters

This section provides a detailed explanation of identifying three class parameters for the model presented in Chapter 3. The first class of parameters pertains to the age profiles of three real income statistics: the mean, mean/median, and Gini coefficients. These parameters will be elaborated upon in Section 2.5.1 (Age profiles). Additionally, in Section 2.5.2 (Time and Cohort effects), I will explore alternative perspectives on these age profiles by considering their implications regarding both time and cohort effects.

In Section 2.5.3 (The growth rates of skill prices), I will discuss the second set of parameters: the growth rates of skill prices (the rental rates of human capital), denoted as g^i. These growth rates are assumed to be constant over the life cycle and specific to each agent type i. These parameters will determine the evolution of skill prices, with the skill price at age $j+1$ denoted as $w^i_{j+1} = w^i_j(1+g^i)$. For each age j and each educational category i, the labour income can be calculated as $w^i_j h_j n_j$ where w^i_j represents the rental rate of human capital, h_j is the quantity of human capital at the beginning of the age, and n_j represents the working time.

The third set of parameters pertains to the depreciation rates of human capital, as explained in Section 2.5.4 (Human capital depreciation rates). These parameters are incorporated into the human capital function as follows: $h_{j+1} = h_j(1-\delta^i) + a(h_j s_j)^\alpha$. In this equation, $\delta^i \in [0,1)$ represents the depreciation rate of human capital for agent type i. $s_j \geq 0$ represents the time invested in human capital production, a denotes the learning ability, and $\alpha \in (0,1)$ represents the curvature parameter.

Finally, in the section on Section 2.5.5 (Wage premiums), I will examine the college-high school wage premium and the college major premiums, explicitly focusing on the wage differentials between STEM and ARTS majors compared to high school graduates. This analysis will highlight the significant impact of choosing a college major on earning disparities. This topic, furthermore, will be acknowledged in Section 3.1 of the subsequent chapter.

2.5.1 Age profiles

Age profiles are essential for calculating three income statistics for the entire sample: mean income, mean-to-median income ratio, and Gini coefficient. In the subsequent chapter, these statistics will play a crucial role in calibrating the distribution parameters of the initial endowments in the model economy. The calibration process aims to minimize the distance between these income statistics derived from the model and the actual data.

To construct the data for the model's life cycle working periods (ages 25-59), I follow a methodology similar to that used in previous studies such as Huggett et al. (2006), Ionescu (2009), Huggett et al. (2011), and Athreya et al. (2019). Specifically, I create synthetic cohorts by employing each year's centred 5-year age bin. For instance, to calculate the

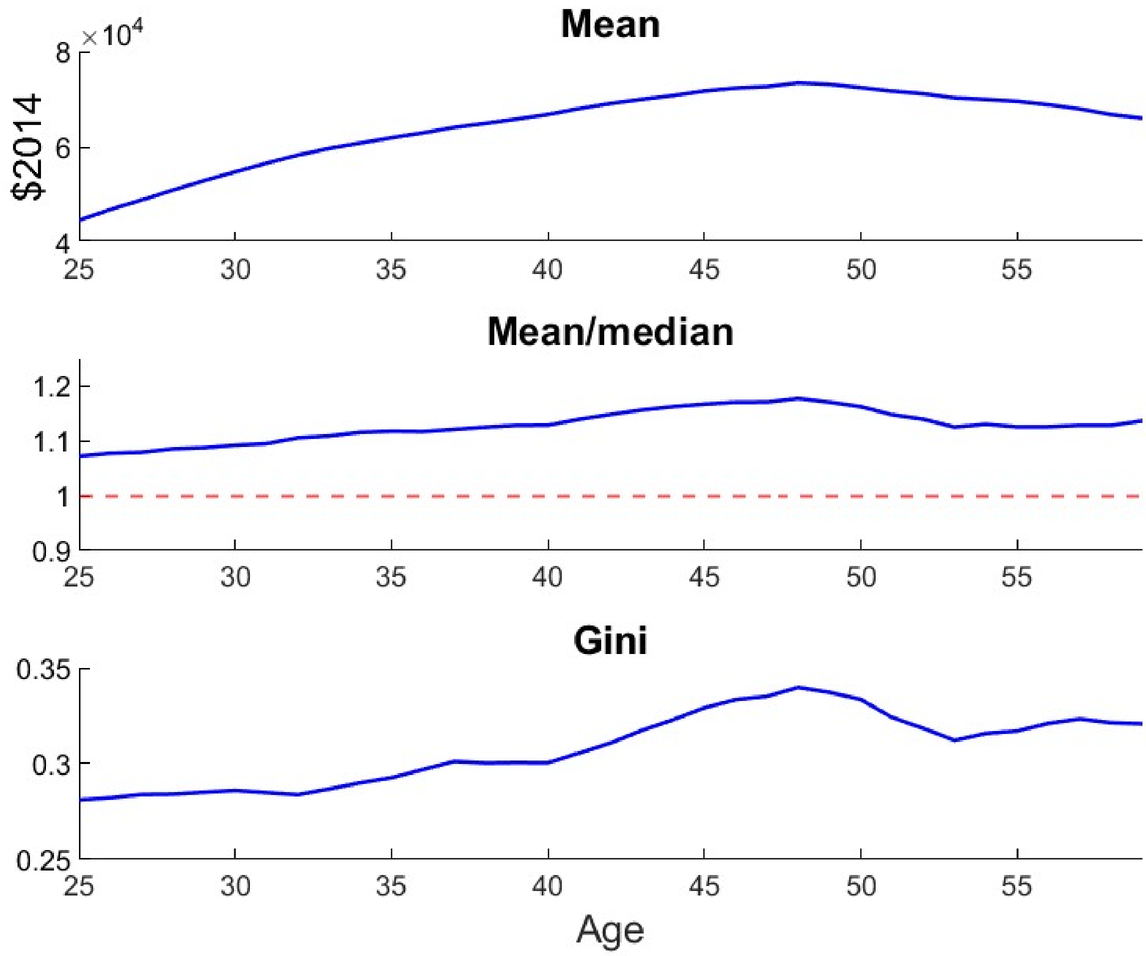

Figure 2.1: Age profiles of mean, Gini, and mean/median of real income for the PSID sample (1968-2019)

annual income statistics for age 25, I use the age bin 23-27, which spans five years centred around age 25. Similarly, for age 59, I utilize the age bin 57-61. This approach allows for capturing the income dynamics and variations over the working period of individuals within the model.

Figure 2.1 presents the life cycle statistics for the PSID sample from 1968 to 2019. This sample comprises predominantly high school graduates (76.9%), with a smaller proportion of individuals in STEM fields (16.6%) and ARTS fields (6.5%). Given the majority representation of high school graduates in the dataset, the mean income profile for the entire sample closely resembles that of the high school group, as depicted in 2.8.

The hump-shaped feature observed in the age-income profile may arise due to a decline in optimal human capital investment towards the later stages of the life cycle. The subsequent chapter will utilize the human capital model to generate this hump-shaped life cycle profile and provide a more comprehensive analysis of this phenomenon.

Figure 2.1 demonstrates that the real income mean/median ratio is more significant than one, indicating that the mean income exceeds the median income across all ages in the life cycle. The median income represents the maximum income received by the lower half of the population when dividing the entire population into two groups: higher-income and lower-income. On the other hand, the mean income accounts for the whole of the people. In other words, the maximum income earned by half of the population is lower than the average income of the entire economy. This measure of inequality, on average, tends to increase throughout the life cycle and reaches its highest value in the age range of 45-50. This finding highlights the rising income disparity experienced by individuals as they progress through different stages of their working lives.

Confirming the earlier findings, Figure 2.2 displays the real income distribution of the population at two specific ages. The figure highlights that the income distribution at age 45 is more skewed to the right than at age 25. This discrepancy can be attributed to the college-high school earning gap observed throughout the life cycle, as depicted in Figure 2.8. Specifically, the age-earnings profiles for STEM and ARTS majors are steeper than those for individuals without a college degree, resulting in higher real income inequality between college and no-college individuals during the middle-aged years, around 45-50.

Figure 2.1 also presents the Gini coefficient as another measure of income inequality. In calculating the Gini coefficient, I utilize Equation (24), which involves sorting the income variable in ascending order and determining the cumulative share of income (Y_i) and the corresponding share of the population (X_i). Equation (24) represented a Gini-style index and was initially introduced by Brown (1994). This equation is practical and efficient when

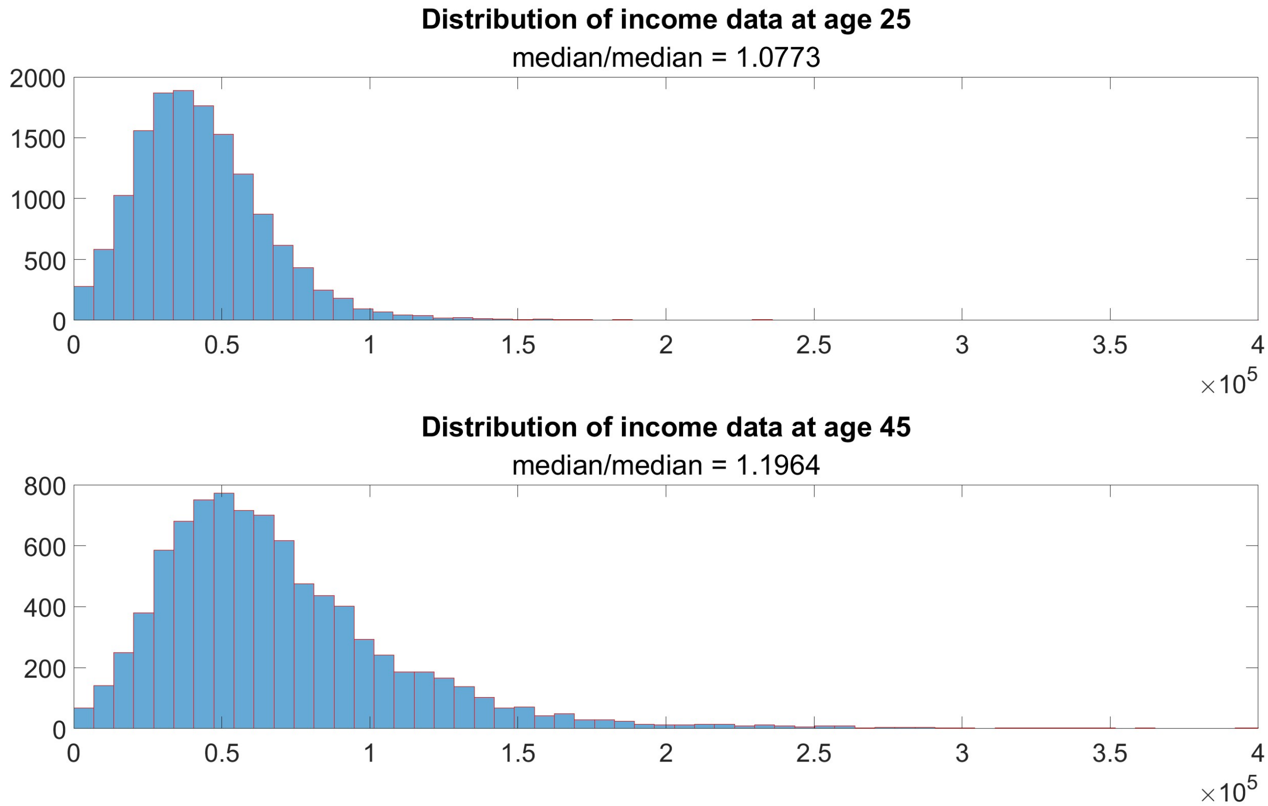

Figure 2.2: Mean/median for two age groups in the life cycle

each observation in the data is associated with its specific weight,

$$Gini = \left|1 - \sum_{i=1}^{n}(X_i - X_{i-1})(Y_i + Y_{i-1})\right|. \tag{24}$$

Equation (25) presents a general method for calculating the Gini coefficient when all observations in the sample have the same weight. It expresses the mean absolute difference ratio between each income pair to twice the average level of all incomes, denoted as $\bar{y}$. In Chapter 3, I will employ Equation (25) as an analogous approach to Equation (24) for determining the Gini coefficient using simulated income data from the model economy. In this simulation, all agents will be assigned the same weight, allowing for a consistent application of the Gini calculation,

$$Gini = \frac{1}{2n^2\bar{y}} \sum_{i=1}^{n}\sum_{j=1}^{n} |y_i - y_j|. \tag{25}$$

The results depicted in Figures 2.8 and 2.2 are consistent with the findings of previous studies, including Huggett et al. (2006), Ionescu (2009), Huggett et al. (2011), and Athreya et al. (2019). These studies have also observed hump-shaped age-income profiles in the U.S. data over the life cycle, alongside an increase in inequality as individuals age. In the upcoming chapter, I will introduce a life cycle human capital model to explain these observed patterns in U.S. data. This model aims to shed light on the underlying mechanisms driving the hump-shaped age-income profiles and the rising inequality throughout the life cycle.

2.5.2 Time and Cohort effects

Some scholars propose modifications to the age-income life cycle profiles illustrated in Figure 2.1. These modifications aim to account for both *Time* and *Cohort* effects, as they can significantly impact individuals' earnings. Time-effect captures the influence of external factors that affect all individuals, such as famines, wars, epidemics, and economic booms or recessions occurring in specific years. On the other hand, the Cohort-effect recognizes that individuals' earnings may be shaped by their particular cohort characteristics, which differ from different cohorts. Factors such as historical events, institutional changes, and peer group socialization can vary based on an individual's date of birth. In other words, the date we observe individuals may have a different influence on their earnings than their actual delivery date. By incorporating both Time and Cohort effects into the analysis, researchers aim to capture a more comprehensive understanding of the various factors that shape individuals' earnings over the life cycle.

To modify the age-income life cycle profiles, Huggett et al. (2006, 2011) employ dummy variables as treatment controls to capture the effects of Time and Cohort. These dummy variables are indicators in an ordinary least squares (OLS) linear regression model. The initial statistical model they consider is as follows,

$$e_{j,t} = \alpha_c \beta_j \gamma_t e^{\varepsilon_{jt}}. \tag{26}$$

Where $e_{j,t}$ is the real mean income of all males in the age bin centred at j in year t. Equation

(26) states that age, time, and cohort effects generate the real mean earnings. α_c, β_j, and γ_t represent the cohort, age, and time effect components. By taking logarithm from both sides of Equation (26) and some abuse of notation, one can decompose this outcome in individuals' birth-year (Cohort), age, and calendar-year (Time) components in a linear, additively separable manner,

$$\ln e_{j,t} = \alpha_c + \beta_j + \gamma_t + \varepsilon_{j,t}. \tag{27}$$

The coefficients of Equation (27) could be estimated by the OLS linear regression model. Then, α_c, β_j, and γ_t will be the coefficients on dummy variables for cohort, age, and time, respectively.

Researchers are often interested in estimating the values of β_j to understand the age profile after accounting for Cohort (α_c) and Time (γ_t) effects. However, a significant challenge in this approach arises from the inability to separately identify the impact of age, time, and birth cohort on the outcome of interest. This challenge arises due to a perfect linear relationship, known as perfect multicollinearity, between age, time, and cohort effects. Specifically, the observation year of an individual is equal to the year of their birth and age ($t = c + j$). Consequently, it is impossible to independently estimate the effects of age, time, and cohort, as they are intrinsically linked. Researchers must make zero Time or Cohort effects assumptions to resolve this issue. In practice, researchers often assume that one of the effects is zero to estimate the remaining effects. This assumption allows for estimating the age profile while considering the impacts of the other two factors.

In this section, I begin by adjusting the life cycle profiles of individuals in my dataset, following the recommendations proposed by Huggett et al. (2006, 2011). Afterward, I will go ahead and present the outcomes of these modifications and explain my decision not to incorporate them into my model.[12] To tackle the concern of perfect multicollinearity, I utilized OLS regressions to estimate the appropriate coefficients individually. This approach allowed me to examine the changes in the age profile of mean real income while considering

[12]These modifications are neither applied by Ionescu (2009, 2011).

either the Cohort-effect or the Time-effect as control variables separately.

$$\ln e_{j,t} = \beta_j + \alpha_c + \varepsilon_{j,t}, \tag{28}$$

$$\ln e_{j,t} = \beta_j + \gamma_t + \varepsilon_{j,t}. \tag{29}$$

Equation (28) represents the Cohort-effect view, where I set $\gamma_t = 0$ for all periods (t). In this analysis, the reference group is the last cohort entering the sample data, which consists of individuals who were 25 years old in 2018. In line with the approach suggested by Huggett et al. (2006, 2011), I focus on the coefficients associated with the age dummy variables, denoted as $\beta_1, \ldots, \beta_{35}$. These coefficients pertain to ages ranging from 25 to 59. Additionally, I subtract the coefficient corresponding to age 38, denoted as β_{14}, from all the age coefficients. This adjustment yields a modified vector of age coefficients, represented as $\tilde{\beta}$, with $\tilde{\beta}_{14} = 0$. Then, these values will be added to the unconditional age-income profile.

Equation (29) represents the Time-effect view, wherein I set $\alpha_c = 0$ for all cohorts (c). In this approach, I consider all individuals observed in 2018 representing the last year of the dataset, as the reference group. To facilitate comparison, I isolate the coefficients associated with the age dummy variable, denoted as β, and subtract β_{14} from each. Subsequently, I incorporate the resulting adjusted age coefficient vector into the unconditional age-income profile.[13]

Figure 2.3 illustrates the age effects on earnings mean using various perspectives. In line with the methodology proposed by Huggett et al. (2006, 2011), the alternative measures are normalized to run through the mean value of each statistic across panel years at age 40. Additionally, all mean profiles undergo normalization by dividing them by the unconditional mean earning value at age 59. This normalization ensures that the unconditional mean earnings equal 100 at the last age, 59.

Figure 2.3 illustrates that all three views qualitatively produce consistent results

[13] In the Cohort-effect approach, the regression has $J \times T$ dependent variables regressed on J age dummies and $J + T - 1$ cohort dummies. The dependent variables are the same in the Time-effect approach, but the independent variables are J age plus T time dummies. In this study, $J = 35$ (age 25-59), and $T = 52$ (1967-2018).

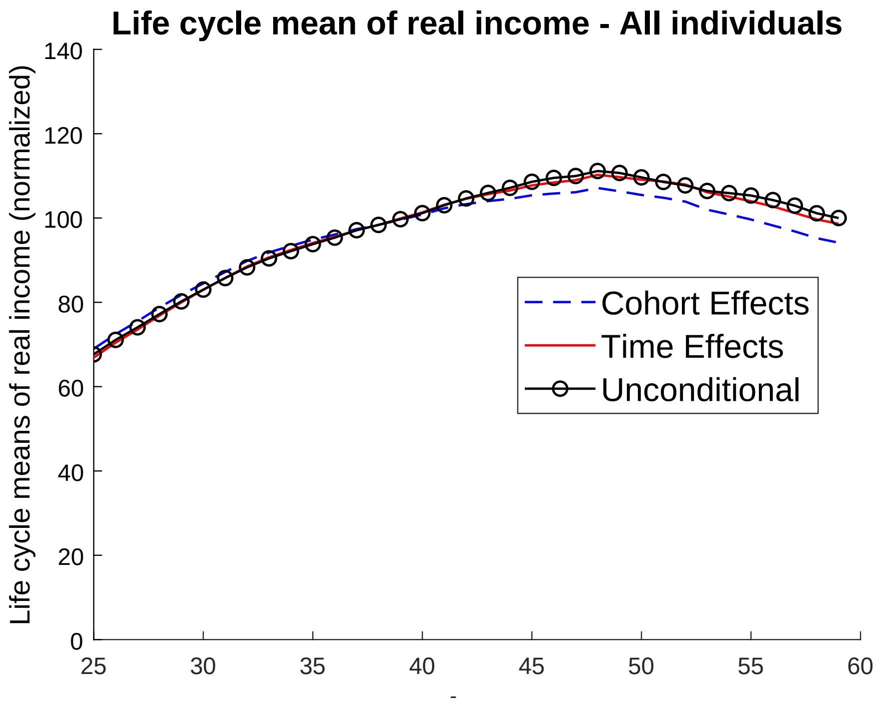

Figure 2.3: Life cycle plots of real income mean for all observations - choice of the y-axis is based on Huggett et al. (2011)

regarding the age effects on earnings mean. However, when examining the quantitative aspects, the Time-effect view closely aligns with the unconditional perspective, displaying nearly indistinguishable outcomes. The Time-effect view, which considers variations over time while controlling for cohorts, exhibits results highly similar to those observed in the unconditional approach. This result suggests that the time-related factors have a limited impact on the overall age-income relationship, reinforcing the stability of the age effect on earnings mean across different periods.

Conversely, the Cohort-effect view shows slight discrepancies from the unconditional perspective. The differences in the Cohort-effect viewpoint to cohort-specific variations in earnings mean emphasizing the significance of the birth cohorts in shaping income patterns over time. Using these distinct perspectives, I have generated the life cycle profiles for the Gini coefficient, mean, and median earnings, depicted in Figures 2.4 and 2.5.

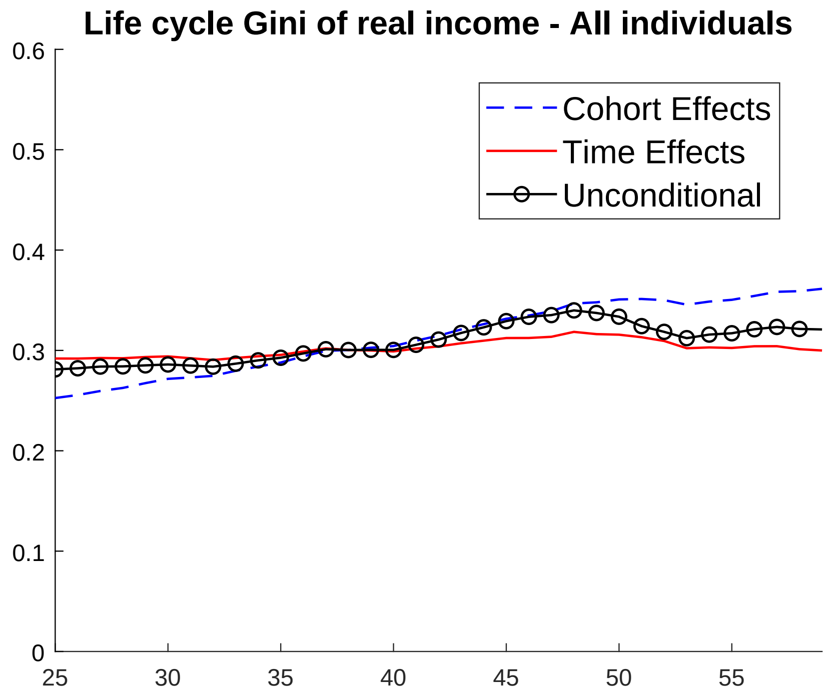

Figure 2.4: Life cycle plots of Gini of real income for all observations - choice of the y-axis is based on Huggett et al. (2011)

Challenges and considerations associated with performing Cohort- and Time-effect modifications.

Huggett et al. (2006, 2011) do not directly address the economic interpretation or significance of the Time and Cohort effects, nor do they explain why the new age-income profile lines intersect the unconditional line at age 40. Additionally, these works do not explicitly discuss the economic significance of the positive or negative deviations from the unconditional profiles.

Furthermore, it is worth noting that there is an ongoing debate and varying perspectives in the literature regarding the appropriate methods for controlling Cohort and Time effects. Several researchers have contributed to the discussion, raising important considerations and proposing alternative techniques. For example, McKenzie (2006), Browning, Crawford, and Knoef (2012), Schulhofer-Wohl (2018), and Fannon and Nielsen (2018) are among the scholars who have offered valuable insights and contributed to the discourse surrounding

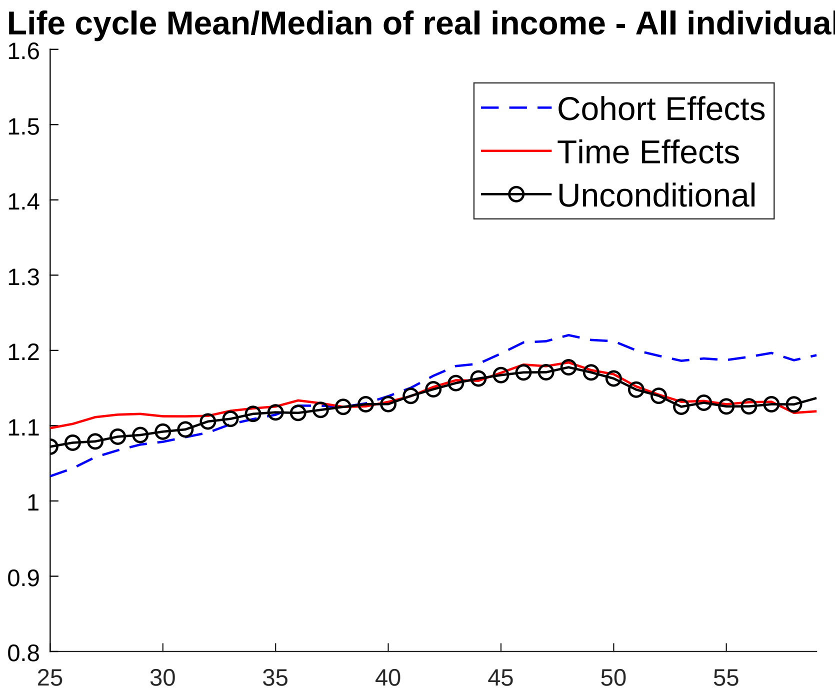

Figure 2.5: Life cycle plots of real income mean/median for all observations - choice of the y-axis is based on Huggett et al. (2011)

the concepts of controlling for Cohort- and Time-effects. Their works explore alternative approaches and discuss potential limitations.

The lack of consensus in the literature regarding Cohort- and Time-effects underscores the complexities in analyzing these factors in economic research. In addition to the challenges we discussed, it is essential to acknowledge that applying Cohort- and Time-effect modifications may not be feasible or suitable for all datasets and variables. In the case of my PSID dataset and the specific age profiles of STEM and ARTS shown in Figures 2.7 and 2.8, there is not a sufficient number of observations within each age-year cell to employ these modifications. This limitation prevents using STEM and ARTS as dependent variables in regression models incorporating age, time, and cohort dummy variables. In summary, due to data limitations and feasibility constraints in my PSID dataset, it is appropriate to stick with unconditional life cycle statistics. This approach allows me to work within the available data and still provide valuable insights into the age-income profiles of STEM and ARTS individuals.

2.5.3 The growth rates of skill prices ($g^{STEM}, g^{ARTS}, g^{no-college}$)

In my research, I adopt the approach and technique employed by Ionescu (2009), Huggett et al. (2006, 2011), and Athreya et al. (2019) to estimate the growth rate of skill price using wage data over time. These studies assume that the growth of skill price (w) is a key factor driving the increase in wage levels (wh) for different cohorts over the years. Consequently, if there is an observed rise in workers' wages, it implies that the price per unit of labour services has also increased.

The technique used to find the growth rate of skill price, g^i.

To conduct my analysis, I followed a systematic process. First, I created a sample dataset by applying the criteria outlined in the Sample selection section, which involves cleaning the PSID data, correcting any inconsistencies in the variables, and selecting individuals based on various controlling variables such as gender, education, occupation, and more. Then, I focused on individuals aged 25-59, grouped them by year from 1967 to 2018, and derived the historical trend of average real wages each year, as illustrated in Figure 2.6. This figure visually represents the changing patterns of average real wages over the selected period. Next, I employed Equation (30) to calculate the growth rate of skill prices for each educational track and for each year spanning from 1967 to 2018. This equation enables me to quantify the rate at which skill prices have changed over time,

$$g_t^i = \frac{\text{average real wage}_t^i - \text{average real wage}_{t-1}^i}{\text{average real wage}_{t-1}^i}, \text{ where } i \in \{ST, AR, NC\}. \tag{30}$$

Finally, to obtain the growth rates of skill prices for each educational category i, I calculate the average of all the growth rates of real wages over the years g_t^i. This process allows me to determine the average rate at which skill prices change within each educational track.

Figure 2.6 provides insights into the real wage growth rates for different educational categories from 1967 to 2018. The analysis reveals several noteworthy trends and patterns. First, the average real wage growth rate for high school graduates is negative over the

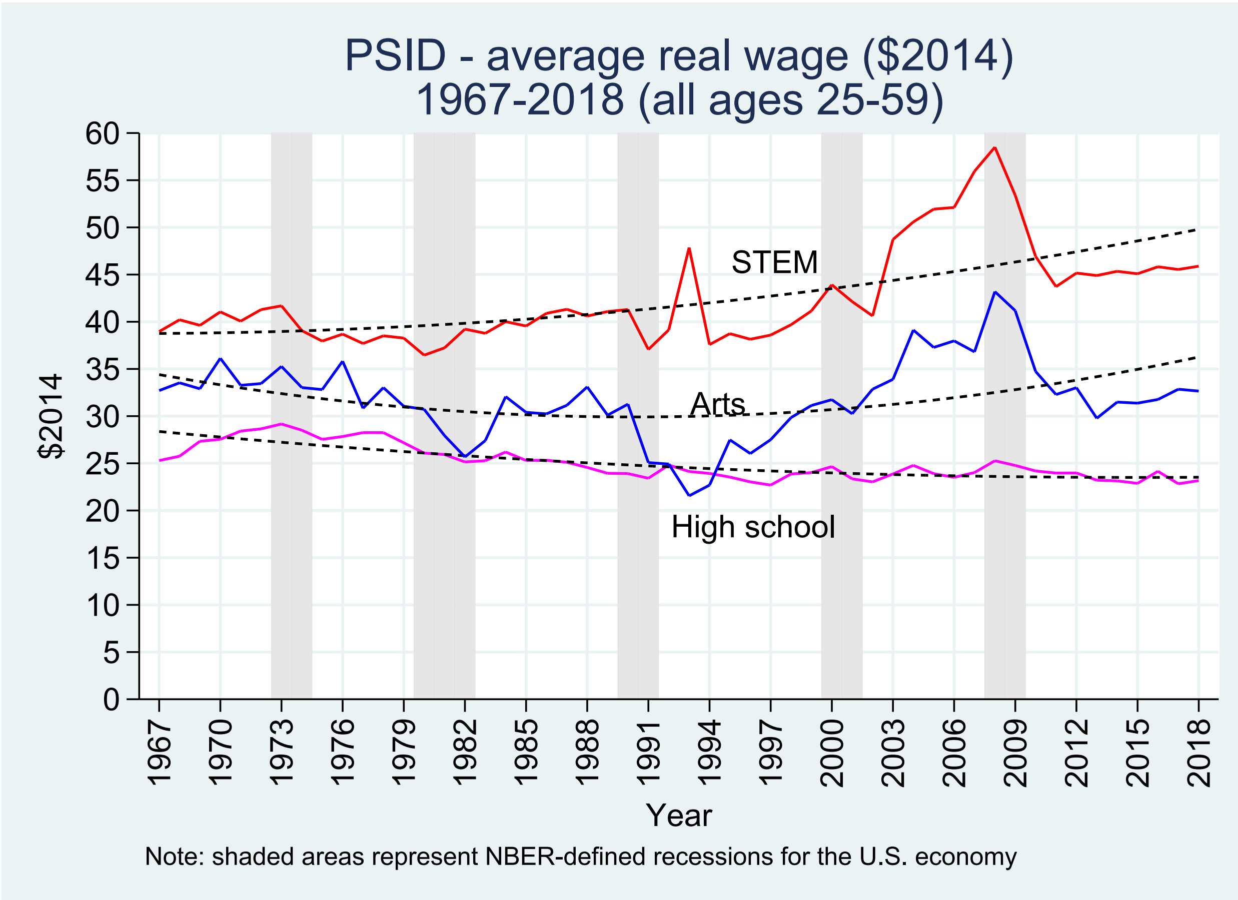

Figure 2.6: Mean real wage for three skill levels - PSID sample 1967-2018

entire period ($g^{NC} = -0.0013$). This finding aligns with the research presented in Bowlus and Robinson (2012), which also observed a declining trend in skill prices for high school graduates.

On the other hand, the real wage growth rates for college graduates exhibit both increasing and decreasing patterns, but the overall trend is positive. For individuals with an ARTS degree ($g^{AT} = 0.0035$) and those with a STEM degree ($g^{ST} = 0.0053$), the average growth rates are positive. This result suggests that, on average, the wages of college graduates have increased over the analyzed period.

Furthermore, Figure 2.6 demonstrates that the gap between STEM and ARTS real wage trends has widened. This widening gap indicates an increase in the wage premium for individuals in STEM fields compared to those in ARTS. This feature will be discussed more in detail in Section 2.5.5 (Wage premiums).

Wage identification problem.

The literature based on the Ben-Porath framework encounters a significant identification problem when estimating the price and quantity of human capital. In the available data, we can observe the wage, denoted as wh. Still, it is challenging to disentangle the specific amount of human capital, represented by h, and its associated price indicated as w. Similarly, while we can observe the growth rates of wages, we need direct visibility into the growth rates of skill prices or the stock of human capital.

This limitation hampers our ability to separately identify and analyze the dynamics of skill prices and the stock of human capital. The inability to disentangle the price and quantity of human capital from the observed wage data restricts our capacity to precisely measure and quantify the changes in skill prices and the stock of human capital over time. Consequently, it becomes more work to provide accurate estimates and assessments of the relative contributions of these factors to wage growth and economic outcomes.

The original Ben-Porath model assumes that the price of human capital remains constant over the life cycle, implying a zero growth rate ($g = 0$). Under this assumption, the wage trajectory over the life cycle reflects the path of human capital. However, this assumption is highly restrictive and needs to capture the complexity of real-world dynamics. The Skill-Biased Technical Change (SBTC) literature challenges the assumption of a constant price of human capital and argues that the relative price of higher-skilled workers has increased significantly during a specific period, typically cited as from 1980 to 1995. According to this perspective, technological advancements and changes in the labour market have led to a demand for higher-skilled workers, resulting in a rise in the relative price of their skills.

During the latter half of the twentieth century, wage inequality in the United States garnered significant attention among scholars. To understand and explain this inequality, a central line of research focused on Skill-Biased Technical Change (SBTC). This perspective posits that technological advancements disproportionately favour workers with higher skill levels, increasing demand for these individuals relative to less-skilled workers. According to the SBTC literature, the nature of technological innovations is skill-biased, meaning that they raise the demand for workers with greater skill levels compared to those with lower skill levels. As a result, occupations that require higher levels of skill experience a rise in the relative prices of their skills over time. This phenomenon occurs under the assumption that the quantities of human capital associated with each level of education and age remain relatively constant.[14]

However, it is essential to recognize that the assumption of a constant stock of human capital may be violated due to cohort effects. New graduates may differ from previous cohorts regarding the quantity of labour services they provide per hour. This discrepancy can arise due to various factors, such as improvements in schooling quality or increased access to on-the-job training opportunities (Inklaar & Papakonstantinou, 2020). In other words, the production functions for human capital may change over time. The more recent production functions may yield a more significant human capital accumulation than previous ones. Consequently, an unobservable factor is at play: the growth rate of the human capital stock over the years.

2.5.4 Human capital depreciation rates ($\delta^{STEM}, \delta^{ARTS}, \delta^{no-colleg}$)

Huggett et al. (2006, 2011), along with Ionescu (2009, 2011), utilize two key pieces of information to estimate the depreciation rates of human capital. These pieces of information are the growth rates of skill prices, denoted as g^i, and the average growth rate of income at the end of the life cycle, g^i_J. Following the same approach, Equation (31) incorporates these two pieces of information and provides a framework to estimate the depreciation rates of human capital. By analyzing the relationship between the growth rates of skill prices and the average wage growth rate at the end of the life cycle, one can derive the depreciation

[14] See the following SBTC literature: Katz and Murphy (1992); Katz and Autor (1999); Autor, Levy, and Murnane (2003); Violante (2008); Goldin and Katz (2008); Autor et al. (2008); Acemoglu and Autor (2011); and Autor et al. (2020), among others.

rates of human capital, δ^i, specific to each educational category $i \in \{ST, AR, NC\}$,

$$\begin{aligned} 1+g^i_J &= \frac{\text{wage}^i_J}{\text{wage}^i_{J-1}} = \frac{w^i_J h^i_J}{w^i_{J-1} h^i_{J-1}} = \frac{w^i_{J-1}(1+g^i) h^i_{J-1}(1-\delta^i)}{w^i_{J-1} h^i_{J-1}}, \\ 1+g^i_J &= (1+g^i)(1-\delta^i). \end{aligned} \tag{31}$$

Equation (31) considers the human capital production evolution as $h_{j+1} = h_j(1-\delta)$, when agents invest no time in human capital at the end of the life cycle, that is, $a(hs)^\alpha = 0$. This setup reveals a critical assumption to identify and estimate the depreciation rate of human capital, δ^i, in the PSID dataset: the human capital is virtually worthless upon retirement. This assumption aligns with the Ben-Porath model of optimal human capital investment. There is a period in an individual's life cycle during which the productivity is constant or decreasing, a so-called "flat spot" range, first proposed in Heckman et al. (1998), also mentioned by Bowlus and Robinson (2012).[15]

To calculate the average growth rate of income at the end of the life cycle, g^i_J, I deviate from the approach employed by Huggett et al. (2006, 2011) and Ionescu (2009, 2011). Instead of using the average growth rate of mean real income over the last ten years of the life cycle, I opt for the average growth rate of the mean real wage, as shown in Equation (31). This modification excludes the effects of working-hour variations in calculating human capital depreciation.

The results for $1 + g^i_J$ indicate gross growth rates of mean real wages over the last ten years of the life cycle. Based on your analysis, the values obtained are 0.9988 for the No-college, 0.9978 for the ARTS, and 0.9963 for the STEM categories. Furthermore, I have obtained the growth rates of skill prices from the previous section as $g^{NC} = -0.0013$ for the No-college, $g^{AT} = 0.0035$ for the ARTS, and $g^{ST} = 0.0053$ for the STEM. By substituting these values into Equation (31), I have calculated the depreciation rates of human capital for each educational category. The results are $\delta^{NC} = 0.000$ for the No-college, $\delta^{AT} = 0.006$ for the ARTS, and $\delta^{ST} = 0.009$ for the STEM categories.

[15] "It exploits the insight that at older ages, wage changes are due solely to changes in skill prices and to depreciation" (Heckman et al., 1998, , page 15).

Following the insights from Keane and Wolpin (1997), the results for the depreciation rates of human capital reveal interesting patterns. Specifically, the findings indicate that the skills utilized by college graduates depreciate at a faster rate compared to those used by high school graduates. This result suggests that the value and relevance of skills acquired through higher education may diminish more rapidly over time. Furthermore, within the college graduate category, the analysis shows that the skills utilized by STEM graduates experience a faster rate of depreciation compared to the skills used by the ARTS category.

Calculating the average gross growth rates $(1 + g_J^i)$ of real wages at the end of the life cycle involves constructing age-wage profiles for each educational category. To obtain these profiles, I employed the same technique outlined in Section 2.5.1 (Age profiles). The resulting age-wage profiles are presented in Figure 2.7.

Additionally, Figure 2.8 illustrates the life cycle real income for three educational groups, presented in 2014 dollars. The figure highlights that, on average, individuals with STEM and ARTS backgrounds experience higher earnings and growth rates throughout their careers than high school graduates. These differences can be attributed to three key factors: skill price, stock of human capital, and hours worked. Notably, the average earnings of ARTS graduates at age 25 are comparable to those of high school graduates. However, the real wage of ARTS individuals at age 25 exceeds that of high school graduates, as shown in Figure 2.7. This higher wage rate is consistent with the higher returns to schooling observed for college graduates. Given that the wage rate for ARTS graduates is higher than expected, the lower-earning levels of ARTS graduates must be attributed to the difference in work hours. Analysis of the PSID dataset reveals that, on average, ARTS individuals work fewer annual hours at age 25 than high school graduates (2,066 hours versus 2,113 hours).[16]

Several scholars have documented the steeper earnings profiles for college graduates. For instance, Belzil, Hansen, and Liu (2017) use a dynamic skill accumulation model of schooling and labour supply that incorporates learning by doing. Their study quantifies potential explanations for steeper age-earnings profiles among more educated individuals. According

[16] ARTS individuals' lower average working hours as new entrants into the job market may be due to their tastes, job conditions, and working environment.

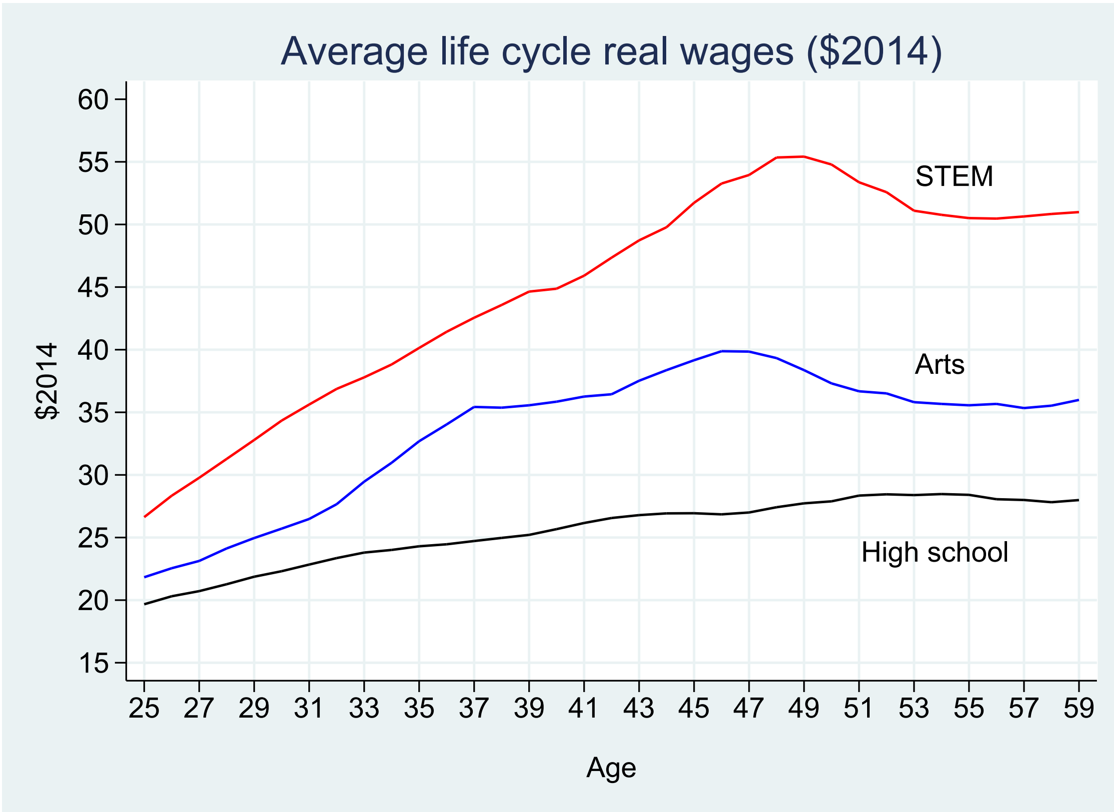

Figure 2.7: Life cycle plots of the mean of real wages for three skill levels

to their findings, two primary factors contribute to the more vertical age-earnings profiles observed for college graduates. First, college graduates tend to have higher ability levels, which result in more significant returns to their work experience than individuals with lower education levels. Second, college graduates have higher productivity of work experience after conditioning on ability endowments and tastes. The authors' findings indicate that the educational background of college graduates contributes to more efficient utilization of work experience, leading to steeper earnings growth over the life cycle.

In addition, Belzil and Hansen (2006) present insights into the determinants of training opportunities and the relationship between formal education and various training activities (on-the-job and off-the-job) in Canada. Their study reveals a positive causal effect of formal education on on-the-job training, even after accounting for unobserved abilities and individual preferences. In other words, individuals with higher levels of formal education, such as college graduates, have more opportunities for on-the-job training, further enhancing

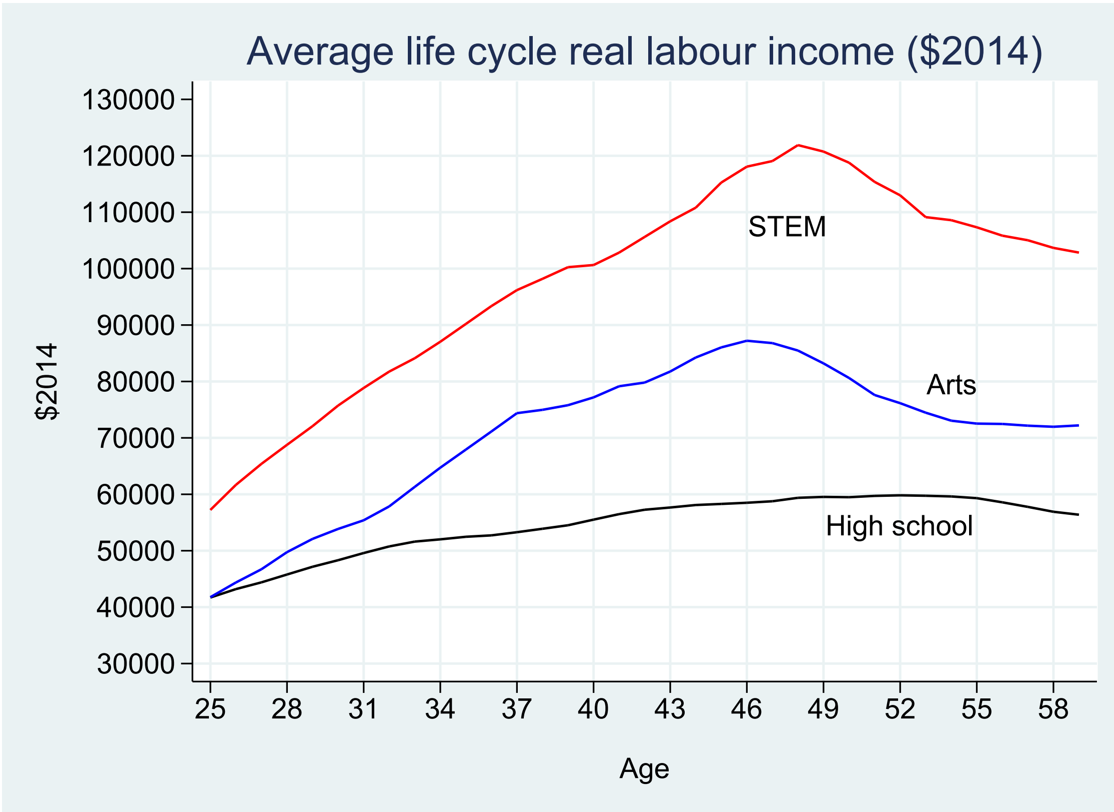

Figure 2.8: Life cycle plots of the mean of real earnings for three skill levels

their workplace skills and productivity.

Moreover, this positive correlation between formal education and on-the-job training is more significant in skill-intensive industries and occupations. In such sectors, the demand for highly educated and skilled workers is higher, leading to more training opportunities for college graduates. Additionally, the study finds a positive association between workplace performance and technology use with the incidence of training among college-educated individuals.

Considering the Skill-Biased Technical Change literature and the relative increase in demand for more educated individuals, it is expected to observe a higher premium and steeper earnings profile for STEM graduates compared to ARTS and high school graduates. The rising demand for skilled workers in STEM fields increases wages and better career prospects for individuals with STEM backgrounds. As a result, the earnings growth trajectory for STEM graduates is likely to be steeper over the life cycle than for those with ARTS and high school education.

2.5.5 Wage premiums

Figure 2.6 highlights the notable disparity in average real wages between STEM and ARTS fields, illustrating the wage premium associated with college majors. To quantify the magnitude of this premium and compare it to the *college-high school wage premium*, I conducted three sets of cross-sectional log-wage OLS regressions, estimated separately for each year t from 1967 to 2018. Equation (32) shows the first regression model:

$$\ln W_{j,t} = \alpha_t + \text{College}_{j,t}\beta_t^c + X_{j,t}\gamma_t + \epsilon_{j,t}, \quad t = 1967 - 2018, \tag{32}$$

where $\ln W_{j,t}$ is the log of the real wage for an individual with age j in year t. $X_{j,t}$ is a vector of individual characteristics containing race and potential work experience dummies. γ_t contains the corresponding coefficients of these variables. $\text{College}_{j,t}$ is a dummy variable describing whether the individual is a college graduate. Vector β_t^c represents the returns from being a college graduate in year t. $\epsilon_{j,t}$ is the error term. The dataset for the first regression contains college and no-college individuals. Therefore, β_t^c represents the wage premium of college graduates over no-college individuals in year t.

Equation (32) includes only two sets of individual characteristics dummy variables (race and experience), as other personal characteristics specific to each educational category, such as education, occupation, gender, and employment status, have already been controlled for through the sample selection process explained in Section 2.4 (Sample selection). In the absence of direct information on experience, I followed Castro and Coen-Pirani (2016) and utilized "potential experience," which represents the number of years an individual of age j could have worked assuming they started school at age 6, completed s years of schooling in exactly s years, and began working immediately after (experience $\equiv j - s - 6$).

Equation (33) represents the second set of regression models, where the dataset includes only STEM and ARTS individuals. The variable $\text{STEM}_{j,t}$ is a dummy variable that indicates whether an individual is a STEM graduate.[17] As a result, θ_t^{st} shows the wage premiums of STEM over ARTS major in each year, t,

$$\ln W_{j,t} = \alpha_t + \text{STEM}_{j,t}\theta_t^{st} + X_{j,t}\gamma_t + \epsilon_{j,t}, \quad t = 1967 - 2018. \tag{33}$$

The regression results of Equations (32) and (33) are presented in Figure 2.9. This figure illustrates the trend of the STEM-ARTS wage gap, also known as the "college major wage premium," over time. It reveals that the wage premium between STEM and ARTS majors has increased over the years, sometimes surpassing the college-high school wage gap." Two significant spikes in the STEM-ARTS wage premium occurred during and after the 1981-1982 and 1990-91 recessions. I conducted two additional regressions to investigate the main drivers behind these changes further. I decomposed the trend of the college premium into separate components for STEM and ARTS graduates, compared to high school graduates,

$$\ln W_{j,t} = \alpha_t + \text{STEM}_{j,t}\beta_t^{st} + \text{ARTS}_{j,t}\beta_t^{at} + X_{j,t}\gamma + \epsilon_{j,t}. \quad t = 1967 - 2018, \tag{34}$$

Equation (34) also includes the dummy variables STEMj,t and ARTSj,t, representing whether an individual is a STEM or ARTS graduate, respectively. The coefficients β_t^{st} and β_t^{at} in Equation (34) capture the STEM-high school and ARTS-high school wage premiums, respectively, over the years 1967-2018 in the sample dataset. Figure 2.10 depicts the results, highlighting that the downward trend in ARTS-high school premiums is the primary factor contributing to the two notable spikes in the STEM-ARTS wage premiums.[18] The observation of declining ARTS-high school premiums and the corresponding spikes in STEM-ARTS wage premiums during recessions aligns with the findings of Oreopoulos, von Wachter, and Heisz (2012). Their research indicates that college graduates with lower earnings potential, determined by their college major and field of study, tend to experience more substantial and enduring declines in earnings during economic downturns

[17] In all regression from 1967 to 2018, the coefficients β_t^c and θ_t^{st} are statistically significant between 1% to 5% level of significance, and their standard errors are less than 0.08, mainly around 0.03 for β_t^c and around 0.05 for θ_t^{st}.

[18] The effect of the fall of ARTS wage premium on college premium is less pronounced because the number of ARTS observations (4,078) in the dataset is less than half of STEM (10,477).

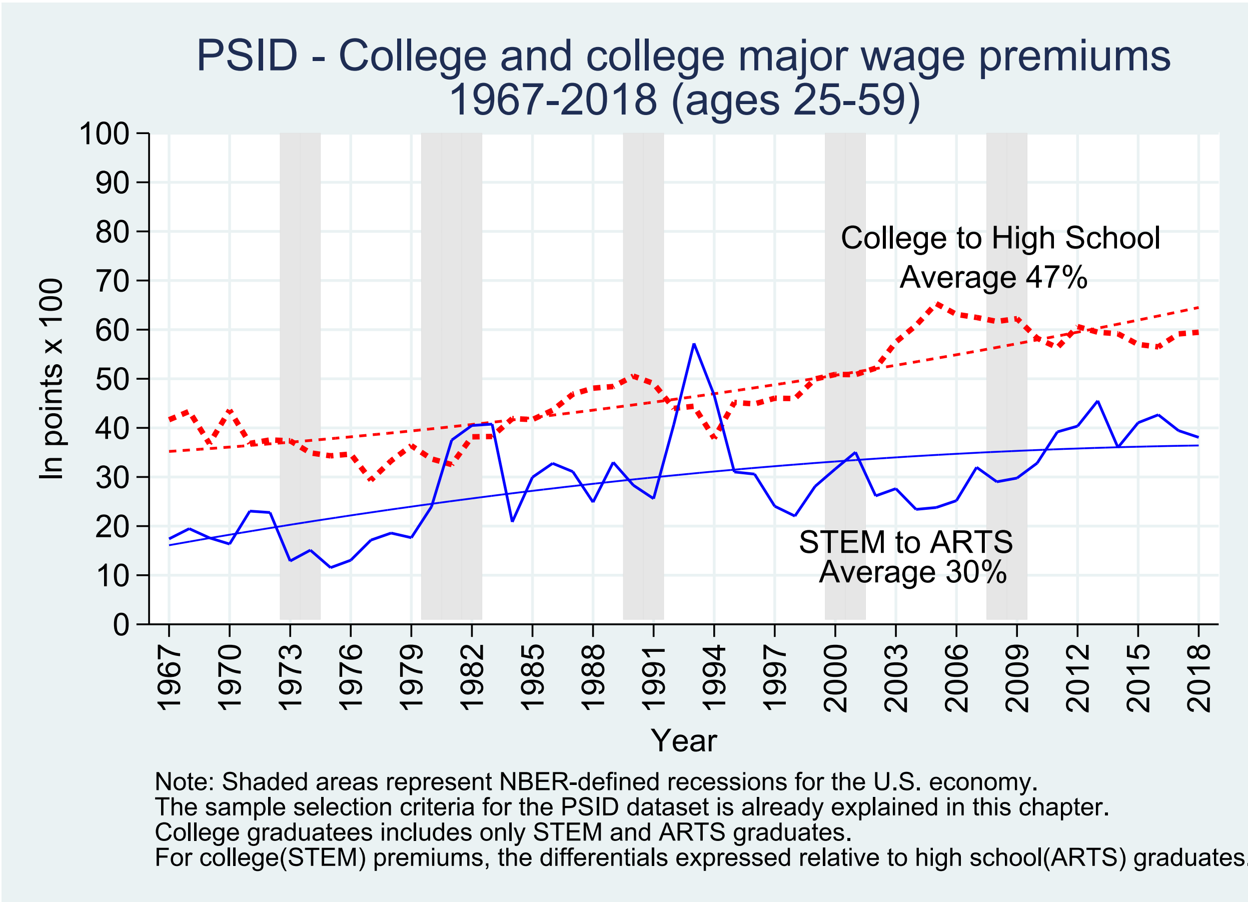

Figure 2.9: College and college major wage premiums -PSID sample 1967-2018

compared to their higher-earning counterparts. This finding suggests that economic recessions disproportionately affect individuals with lower-earning college degrees, which could contribute to the observed patterns in wage premiums between educational categories.

2.6 Summary and conclusion

This chapter utilizes annual income and demographic data from the 1968-2019 PSID dataset to derive three sets of information. These pieces of information are crucial for running the economy model and matching it to the data in the next chapter. The first set involves the life cycle statistics for all individuals, including measures such as the mean of real labour

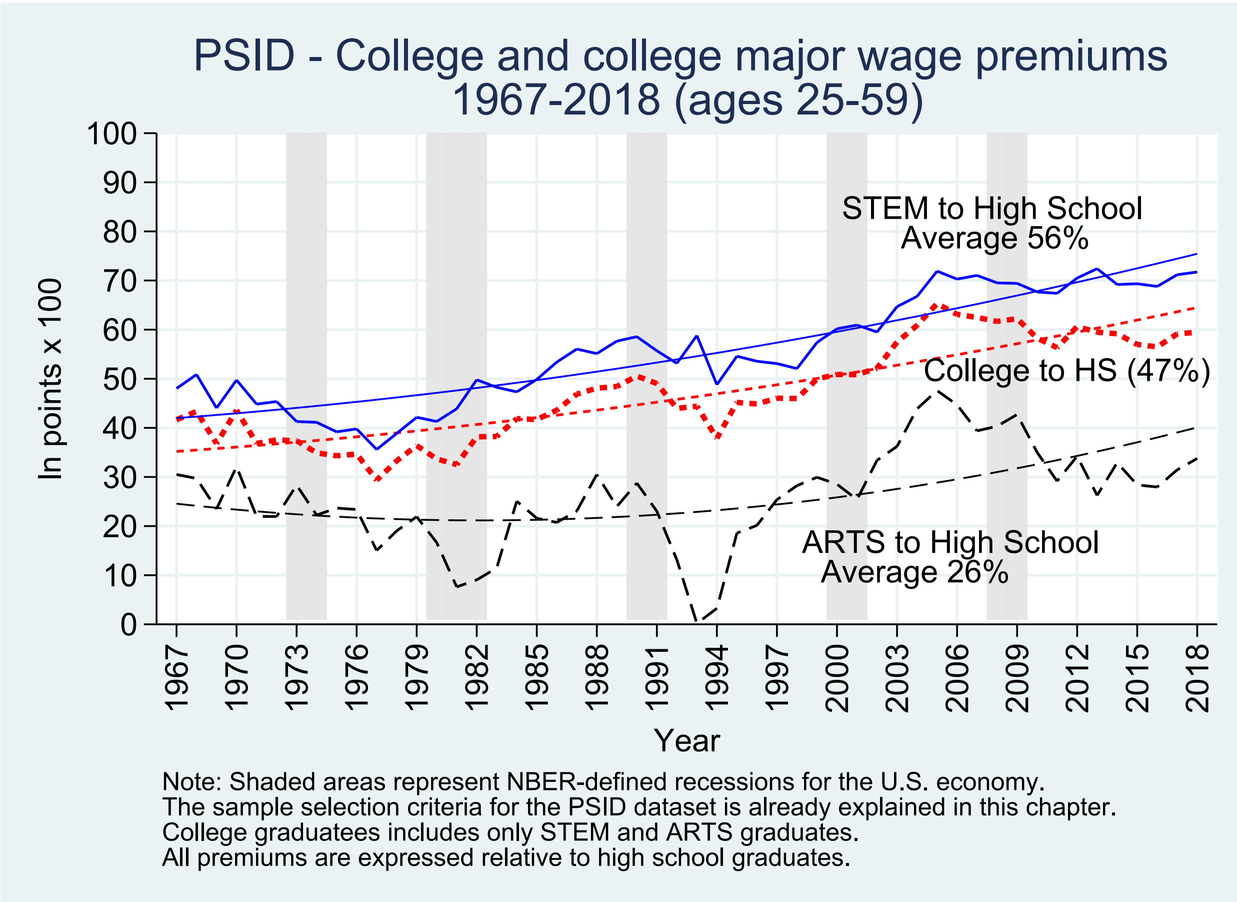

Figure 2.10: College and college major wage premiums -PSID sample 1967-2018

income, the mean/median ratio, and the Gini coefficient. The second set pertains to wage parameters, specifically the growth rates of skill prices. Lastly, the chapter determines the parameters of the human capital accumulation function, namely the depreciation rates of human capital. These sets of information are essential for analyzing and understanding the dynamics of the economy concerning income and educational factors.

The utilization of the PSID dataset is motivated by its longitudinal nature and the availability of comprehensive economic and demographic information on individuals in the United States. The dataset offers detailed data on families and individuals, focusing on the “Head" of the household. This longitudinal aspect enables researchers to track individuals over an extended period and study their economic activities and outcomes. These distinctive features of the PSID dataset are essential for accurately identifying individuals within three specific educational categories (STEM, ARTS, no-college) and conducting a thorough analysis of their economic and academic trajectories.

After a rigorous sample selection process, the final dataset consists of 63,108 person-year observations covering the income periods from 1967 to 2018. The dataset is further categorized into three educational categories: college STEM, college ARTS, and high school graduates. Specifically, there are 10,477 person-year observations for college STEM graduates, 4,078 person-year observations for college ARTS graduates, and 48,553 person-year observations for high school graduates.

The age-income profile serves as the basis for deriving various life cycle statistics for all individuals in the sample. These statistics include the mean, mean/median ratio, and Gini coefficient of real labour income. The next chapter will subsequently use these statistics to determine the optimal parameters of the initial distribution in the simulated economy model. To estimate the human capital parameters, I analyzed the mean real wages for individuals aged 25-59 from 1967 to 2018. From this analysis, I obtained the growth rates of skill prices as follows: $g^{ST} = 0.0053$, $g^{AT} = 0.0035$, and $g^{NC} = -0.0013$. These growth rates serve as important parameters in the model. Using these growth rates, I further calculated the depreciation rates of human capital. Based on the chosen growth rates, the estimated depreciation rates are $\delta^{ST} = 0.009$, $\delta^{AT} = 0.006$, and $\delta^{NC} = 0.000$.

As demonstrated in this chapter, the age-wage profiles for individuals in the STEM and ARTS categories are higher and steeper than those without a college certificate. Several factors contribute to this finding, including the difference in individuals' ability levels. Those with higher learning abilities tend to accumulate more human capital through college education, leading to higher wage profiles. The initial human capital stock disparity may also affect the observed wage profiles. Individuals with higher initial human capital stock tend to accumulate more human capital throughout their life cycle, which translates to higher returns when they enter the workforce.

The model developed in the subsequent chapter aims to uncover a mechanism that can account for the disparities in wage and earnings profiles among individuals with different educational backgrounds. Furthermore, it seeks to serve as a foundation for conducting policy experiments. This mechanism must align with the empirical observations and patterns discussed in the human capital literature.

One of the key observations is that individuals tend to allocate a significant amount of their time during their early years to acquire skills through education and training. The model should capture this pattern of skill acquisition during youth.

Additionally, the model must replicate the steeper age-earnings profiles typically observed for individuals pursuing higher education levels. This feature reflects the higher returns associated with investing in higher schooling and accumulating specialized skills and knowledge over time.

Furthermore, the model should account for the finding that the present value of earnings, on average, increases with a measure of an individual's learning ability. This indicates that individuals with higher learning abilities tend to have higher lifetime earnings due to their capacity to acquire and apply knowledge more effectively.

By incorporating these key empirical regularities into the model, I will develop a framework that explains the differences in wage and earnings profiles across educational categories and allows for examining various financial aid policy experiments to assess their potential impact on individual decisions on college enrollment and career choices.

Chapter 3

The Model and Policy Experiments

3.1 Introduction

Earnings disparities among college majors have experienced a significant increase over time.[1] Altonji et al. (2012) utilized data from the 2009 American Community Survey (ACS) to demonstrate that disparities in earnings among different fields of study in college are similar to the wage gap between individuals with a college degree and those with only a high school education, commonly referred to as the *"college-high school wage gap."* James (2012) uses the Current Population Survey (CPS) data and shows that the choice of college major is becoming a more vital determinant of wage variation than the choice of pursuing a four-year degree in college. With the higher return to specific fields of study and in response to concerns about students' readiness for the workforce, periodic policy reports call for a significant increase in college graduates in STEM fields. Examples are executive reports of the President's Council of Advisors on Science and Technology.[2]

The main concern of this chapter is to investigate the main determinants of college

[1] For review, see Altonji, Arcidiacono, and Maurel (2016); Altonji et al. (2012); Altonji, Humphries, and Zhong (2022); Altonji, Kahn, and Speer (2014, 2016); Gemici and Wiswall (2014); Xue and Larson (2015).

[2] See The President's Council of Advisors on Science and Technology (PCAST) Executive Report 2020, PCAST Executive Report 2016, PCAST Executive Report 2012, and PCAST Executive Report 2010, (last accessed December 2023).

enrollment and, more specifically, the attendance of high school graduates in two primary college majors, STEM and ARTS, as the representative of higher and lower-paid majors in the labour market. In this regard, first, I develop a partial equilibrium heterogeneous agent life cycle model as a generalization of the *human capital model* developed by Ben-Porath (1967) and updated by Huggett et al. (2006), Ionescu (2009), Athreya et al. (2019), Badel, Huggett, and Luo (2020), and Wu (2021). It combines a standard life cycle consumption-savings problem in which agents have a portfolio choice with a human capital accumulation model in college studies and on-the-job training.

My model is similar to that in Ionescu (2009). However, I have expanded upon her work by incorporating additional elements. First, my model contains two fields of study: STEM and ARTS. Second, I introduced work and investment time in human capital as components of the agents' objective function. This addition allows for a more comprehensive analysis of the factors influencing individuals' decision-making processes. Third, I incorporated functional forms for merit-based scholarships into the existing model. Fourth, the model provides proxies for college dropout features. The criteria for college graduation consist of a minimum time to study and a minimum increase in the initial human capital endowment during college. By incorporating these expanded elements into the current model framework, I aim to provide a more comprehensive and realistic analysis of the factors influencing college enrollment, human capital investment, and income distribution across fields of study.

In the model, the agents are heterogeneous. They differ concerning an index of ability to study (college preparedness), initial ability to earn (initial stock level of human capital), and initial resources (initial asset or expected family contributions for college). The educational categories in the model are distinguished based on the type of human capital being acquired. These categories exhibit two primary distinctions: the growth rates of skill prices (human capital rental rates), g, and the depreciation rates of human capital, δ. These model parameters are obtained from the PSID dataset, and further details can be found in Chapter 2. By incorporating these elements and deriving relevant parameters from the PSID dataset, the model aims to capture individuals' heterogeneity in college preparedness, initial human capital, and financial resources.

The model is structured into twelve periods, each representing a five-year interval, starting from age 20 when high school graduates decide their educational path, either by entering the workforce or pursuing majors in ARTS or STEM fields. All individuals retire at the age of 60. During college, students decide how much to save and allocate their one unit of time endowment to study and work, leading to an optimal human capital level for the next period. Also, they take student loans which must be repaid within two model periods, representing the standard ten-year repayment period post-college.

Students may receive merit- and need-based grants during college based on their ability and initial asset levels. They can finance their studies using this financial assistance, initial assets, student loans, and earnings obtained from working in the market as students. Agents can save their assets in the market and receive interest on their savings in the following period. Also, they can borrow from the market as needed throughout their working periods.

The career path selection in the model is driven by the lifetime utilities associated with each available option. Therefore, the agent's problem needs to be solved for each potential career path. To understand the main factors in the model that affect an agent's decision to choose the desired path, one needs to focus on the factors that could affect the lifetime earning process. Some of these factors are the parameters specific to each career path. As explained in Section 2.5 of the previous chapter, these parameters are directly derived from the PSID dataset.

The first set of these parameters is the growth rates of skill prices or the rental rates of human capital (g^i), and the second set of parameters are the depreciation rates of human capital (δ^i), $i \in \{ST, AT, NC\}$. As shown in Section 2.5.3 of the previous chapter, the results from the PSID reveal the following relationships among the three educational categories: $g^{ST} > g^{AT} > g^{NC}$, and $\delta^{ST} > \delta^{AT} > \delta^{NC}$. These relationships are the core criteria that differentiate educational categories in the model.

The findings from solving the benchmark economy confirm that only individuals with higher ability levels are motivated to enroll in college. This result can be attributed to the college's central role within the model. The college education process transforms the human capital of high school graduates into a specialized form known as college-type human capital, which possesses two crucial characteristics. The first characteristic of college-type human capital is its higher rental rates or skill prices in the labour market. The second feature of college-type human capital is its higher depreciation rate compared to the no-college type of human capital. This feature implies that the skills and knowledge obtained through college education tend to depreciate faster over time in STEM and ARTS fields than in no-college individuals.

Results show that career choice is determined primarily by ability, not initial human capital or the initial asset, because the growth of human capital and wages is higher for higher-ability people, as predicted by Ben-Porath's model, explained in Chapter 1. The economic explanation lies in the trade-off between skill price growth and high human capital depreciation. The growth rates of skill prices for college-type are higher than that of a no-college path. However, their human capital depreciates faster. Individuals must possess a higher ability level to compensate for the higher depreciation rates of college-type human capital. Individuals with lower abilities cannot accumulate enough human capital to offset the depreciation effect. The model results show that, on average, the higher learning ability individuals choose a college, and the highest ability agents choose the STEM path. Consequently, STEM individuals accumulate a higher stock of human capital and enjoy higher wages, earnings, and consumption over the life cycle.

I fit my model using two sets of information. The first set consists of key moments from three life cycle income distribution statistics, specifically the mean, Gini coefficient, and the mean/median ratio, obtained from all individuals' working periods. The second information set comprises the STEM and ARTS enrollment rates derived from the PSID 1968-2019 surveys dataset.

Once my model fits the data, I utilize it to assess the potential impacts of ten policy experiments on college enrollments. Simulation of the model allows the implementation of ten experiments. These experiments included a 30% increase in merit-based scholarships, a 30% increase in need-based grants, a 30% decrease in tuition and fees, a 35% rise in the student loan limit, three extensions to the distribution of merit-based scholarships and three other versions of distributing the need-based grants. By employing these policy experiments, I could estimate the likely effects of these policy changes on college enrollment rates.

In the first policy experiment, I increase the limits of merit-based scholarships by 30%, equally applying to all ability levels. Choosing this percentage of increase is inspired by the relevant literature in Chapter 1, explaining the effects of the various state-sponsored merit-based scholarships. This experiment targets individuals only with high and medium abilities. The results show a 2.4 percentage point increase in college enrollments.

The second policy increases the limits of need-based grants by 30%. Also, this percentage increase aligns with the literature in Chapter 1, explaining the effects of the various need-based grants. The poorest individuals benefit from this policy, and the more affluent individuals receive no grants. The impact of the policy is close to the previous one, and the results show a 5.3 percentage point increase in college enrollment. The ARTS category absorbs all of this increase, mainly from low-asset families.

In the third experiment, the four-year college tuition and fees are decreased by 30%. This policy targets all individuals irrespective of their ability or initial assets. In other words, more students will benefit from this policy. This policy delivers a nearly ten percentage points increase in college enrollment compared to the benchmark economy. Decomposing this change in enrollment shows that the ARTS category captures around 97% of the total gain.

The fourth experiment is related to the government student loan program. In this policy experiment, the maximum level of the governmental loan is increased by 35%. This increase is similar to the real-life policy in 2008 when the loan limit increased from 23,000 to 31,000 dollars. This policy has the lowest effect in increasing total college enrollment by 0.7 percentage points, all in ARTS.

To continue the merit-based scholarship distribution, I introduced the subsequent modifications, crafting three extensions to Policy 1: the 30% augmentation in merit-based scholarships. Across all three new scenarios, I maintained the maximum scholarship amount at parity with the benchmark economy. I extended the ability level threshold requisite for scholarship reception in the initial experimental variation. The second extension broadened the eligibility threshold for attaining a full scholarship. The third extension encompassed the expansion of both thresholds.

Outcomes reveal that the strategy of broadening the eligibility threshold and containing individuals with medium ability under the coverage of full scholarships yields a superior impact on college enrollment, proving to be a more cost-effective policy when contrasted with the simple merit-based scholarship distribution (Policy 1), which involves a universal 30% increase in merit-based scholarships across all ability levels. The twofold-coverage-expansion experiment results in a 5.4 percentage point upswing in college enrollment, surpassing the 2.4 percentage point increase achieved by Policy 1. Moreover, this expansion policy proves to be more efficient than Policy 1, yielding a \$4.7 gain in the present value of the lifetime college income per dollar of additional policy cost, instead of Policy 1's \$2.2 gain.

In parallel with the extensions applied to the foundational merit-based financial aid policy, I conducted three novel expansion policy experiments aligned with the basic need-based grant policy (Policy 2 - a uniform 30% increase in need-based grants, evenly distributed among all eligible individuals). Interestingly, the outcomes of these experiments mirror the findings of the prior three new policies. Expanding the coverage for total need-based grants and the eligibility threshold proves more advantageous than the simple need-based grant policy. Remarkably, the experiment involving a twofold expansion of the need-based policy yields a substantial 6.4 percentage point surge in college enrollment, outperforming the 5.3 percentage point increase achieved by Policy 2. Furthermore, this extended policy emerges as more efficient than Policy 2, yielding a \$3.2 gain in income per dollar of additional policy cost, as opposed to Policy 2's \$2.8 gain.

The findings underscore that the most potent strategy for increasing college enrollment is the reduction of tuition and fees (Policy 3), with particularly pronounced impacts for ARTS students. This policy ushers in a notable 9.9 percentage point surge in college enrollment, with 0.3 and 9.6 percentage points increase in STEM and ARTS enrollments, respectively. Nevertheless, Policy 3 is not cost-efficient because of its non-targeted nature, disbursing financial aid to individuals who may not be in financial need (such as students from affluent families) or those possessing lower levels of learning aptitude. In contrast, policies focused on broadening the scope of eligible students who receive full tuition and fees financial aid (whether through need-based or merit-based criteria) and/or expanding ability or initial-asset thresholds demonstrate superior efficiency compared to Policy 3. These strategies effectively heighten college enrollment while maintaining greater cost-effectiveness than other policy alternatives.

This chapter covers the benchmark model, the results, and the relevant policy experiments. In section 3.2, I will discuss the theoretical model and its components in detail: preferences, human capital accumulation at school and on-the-job training, earnings, agent's problem by choosing various study paths, repayment of college loan, and the decision-making criteria for college enrollment in fields of ARTS or STEM.

Section 3.3 will explain how to map the model to the data. More specifically, it will discuss the procedures to assign values to the relevant model parameters in detail. Then section 3.4 covers the computation procedure and its algorithm, followed by simulation detail in section 3.5. For simulation, first, I determine the distribution of initial endowments in the benchmark model economy. This distribution is determined by nine parameters: the mean, standard deviation, and cross-correlations of three initial endowments. These parameters are estimated jointly by minimizing the distance between 23 moments of the life cycle income distribution of PSID data and the model: mean, Gini, and the mean/median ratio of seven working periods of all individuals and the enrollment rate in STEM and ARTS.

In section 3.6, I will discuss targeted moments, represent how the model fits the data regarding these moments, and explain the procedure to obtain the measure of goodness of fit of the model. Section 3.7 will present the paper's results, such as who goes to study STEM or ARTS majors in college in terms of ability, initial human capital or initial assets.

Section 3.8 will discuss various scenarios of policy analysis: an increase in merit-based scholarships, an increase in need-based grants, a decrease in tuition and fees, and an increase in student loan limit. Finally, section 3.9 summarizes this chapter.

3.2 Theoretical model

3.2.1 Model environment

The model environment is a life cycle economy with heterogeneous agents. Age is discrete and indexed by $j = 1, \ldots, J, \ldots, E$. Each model period represents five years, and agents live for 12 periods ($E = 12$), corresponding to 20–79 years of age. The work-life of an individual starts from age 20 when they can potentially start working, and last for eight periods ($J = 8$) equal to 40 years and retire at age 60.[3]

My model abstracts from childhood and early education. The model is based on the one-time college enrollment decisions young adults make after graduation from high school. All talents and capabilities that model agents inherited or accumulated in childhood and high school are reflected in their learning ability and the human capital when they graduate high school.[4]

Model periods. The decision to employ twelve model periods to represent 60 years of age is primarily driven by the aim of reducing computational complexity. The model's computations and simulations become more manageable and computationally efficient by dividing the time frame into twelve discrete periods. Furthermore, five years per model period aligns with the average reported completion time for undergraduate studies. Many sources

[3]The main reason for using a terminal period below the traditional retirement age is the high attrition of higher ages in the PSID. Many other scholars did the same. Ionescu (2009) and Athreya et al. (2019) set the last working year at age 58. Kambourov and Manovskii (2009) restrict the PSID sample to male heads of households aged 18-61 who are not self- or dual-employed. Wallenius (2011) assumes that the individual works until age 62. Also, Huggett et al. (2011) choose the last working age at 60 and mention that labour force participation falls near the traditional retirement age for reasons abstracted from their model.

[4]For the various aspects and modelling of the human capital accumulation process during childhood and early education, see the following papers, among others, Attanasio, Cattan, and Meghir (2021); Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020); Schoellman (2016); Jackson, Johnson, and Persico (2016); Dynarski, Hyman, and Schanzenbach (2013), and Chetty et al. (2011).

indicate that individuals typically take around five years to complete their undergraduate degrees. Thus, this time frame provides a realistic representation of the duration of college education within the model.[5,6] Additionally, the five-year model periods are a good fit for the standard ten-year repayment time for student loans. With a repayment period typically set at ten years post-college, the five-year model periods allow for two periods dedicated to the repayment of student loans, which aligns with the standard repayment timeline.

Life cycle stages. In the model, the life cycles of college and no-college paths have four and two stages, respectively. Individuals who choose a college career path go to college for five years ($j = 1$). After graduation from college, agents enter into the repayment phase ($j = 2, 3$). They work and pay back all their student loans within ten years. Then, in the post-payment phase ($j = 4, \ldots, 8$), agents continue to work for the next 25 years and have no debt to pay. In the last stage ($j = 9, \ldots, 12$), they retired and lived for 20 years.

I incorporated retirement into the model based on several considerations. Firstly, retirement introduces a motive for saving, as individuals need to accumulate enough financial resources to sustain their desired standard of living during their non-working years. Secondly, retirement impacts agents' consumption behaviour within the model. As individuals transition from working to retirement, their income streams change, and they adjust by smoothing their consumption patterns accordingly.

Lastly, the inclusion of retirement aligns with available data and empirical observations.

[5]The National Student Clearinghouse Research Center examines the time to degree completion for a cohort of students who earned a bachelor's degree as their first four-year degree between July 1, 2014, and June 30, 2015. This report indicates that the average time enrolled for bachelor's degree earners is 5.1 years. Source: National Student Clearinghouse Research Center (2016) Time to Degree: A National View of the Time Enrolled and Elapsed for Associate and Bachelor's Degree Earners, (last accessed December 2023).

[6]According to the National Center for Education Statistics (NCES), the overall four-year graduation rate for first-time, full-time undergraduate students who began seeking a bachelor's degree in the fall of 2013 was 45 percent. The same 2013 entry cohort's five-year and six-year graduation rates were 60 and 62 percent, respectively. Source: U.S. Department of Education, National Center for Education Statistics (NCES), Annual Reports, Digest of Education Statistics 2020, Table 326.10., (last accessed December 2023). Some other students complete their bachelor's studies in more than six years. Another report by NCES shows that 26% of 2015–16 first-time bachelor's degree recipients completed their degree in more than six years. This report shows that the weighted average of time to degree is nearly five years. Source: U.S. Department of Education, National Center for Education Statistics (2019), Baccalaureate and Beyond (B&B:16/17): A First Look at the Employment and Educational Experiences of College Graduates, 1 Year Later, Table 2, (last accessed December 2023).

By incorporating retirement, the model can better capture real-world phenomena and ensure its results align with empirical evidence. Overall, adding retirement to the baseline Ionescu's model addresses the motives for saving, captures the influence of retirement on consumption behaviour, and enhances the model's alignment with real-world data and observations.

Table 3.1 shows the life cycle stages, the corresponding model periods, and the length of years for various phases of college and non-college paths.

Table 3.1: Life cycle stages

Stages	Periods	Years	Ages	College path	No-college path
1	1	1-5	20-24	College/ Student loan	
2	2-3	6-15	25-34	Work / Loan repayment	Work
3	4-8	16-40	35-59	Work	
4	9-12	41-60	60-79	Retirement	

I allow for three potential sources of heterogeneity across agents at the beginning of life: their initial assets (x_1) or the family (parental) resources, their initial human capital stock (h_1), and their endowed learning ability (a), a trait that allows agents to learn more in college and remains constant after graduating from high school. I draw these characteristics using a joint distribution, $F_{A,H,X}(a, h, x)$.

At the core of my model are agents' decisions, whether directly participating in the market or pursuing higher education in STEM or ARTS disciplines. Figure 3.1 illustrates the decisions and the timing of potential phases for a typical agent in the model. At the beginning of the first period, agents make a one-time decision: whether to enter college and select a major. Considering their initial attributes (a, h, x), individuals who have completed high school choose between enrolling in college or directly entering the workforce. Furthermore, if the decision is to attend college, the agent selects between STEM and ARTS majors.

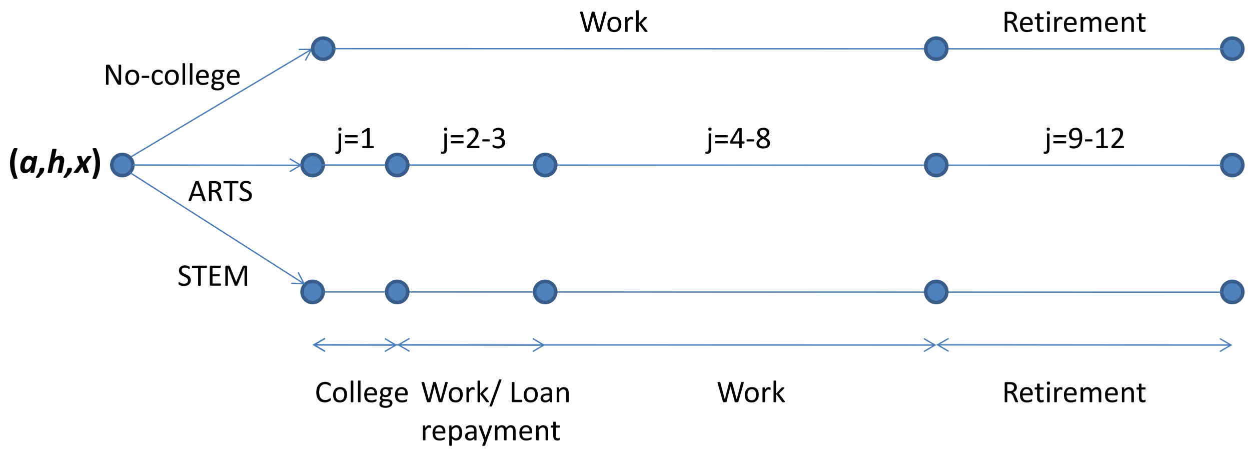

Figure 3.1: Timing of an agent's relevant life cycle phases with the initial endowments (a, h, x)

3.2.2 Preferences

The utility function of agents is assumed to be additive and separable between consumption and work-study time. The preference is a "constant Frisch elasticity" type (CFE preference). Individuals' present value of utility over the life cycle is

$$\sum_{j=1}^{E} \beta^{j-1} \left[\ln(c_j) - \psi \frac{(n_j + s_j)^{(1+\frac{1}{\kappa})}}{(1+\frac{1}{\kappa})} \right], \tag{35}$$

where β is the discount factor, n is labour supply, and s is time invested in human capital accumulation in studying or on-the-job training. The period utility function over consumption is in log form, indicating that the coefficient of relative risk aversion equals 1. Parameter ψ captures the level of disutility from work and study time, and $\kappa > 0$ is the (constant) Frisch elasticity.

3.2.3 Human capital accumulation at school and on-the-job training

In my model, formal schooling at college and post-schooling on-the-job training accumulate human capital. Agents optimally allocate time to market work, n_j and invest in human capital, s_j. The quantity of human capital evolves by $h_{j+1} = h_j(1 - \delta^i) + f(h_j, s_j, a)$ where $\delta^i \in (0, 1)$ is the depreciation rate of the human capital which depends on an individual's education track, $i \in \{ST, AT, NC\}$, as a college path in the fields of STEM/ARTS or no-college track. The functional form of human capital accumulation is the same for all agents and life cycle periods. It follows Ben-Porath's model in discrete-time, which is abstract from the "learning by doing" notion (accumulating human capital through working experience), as explained in Appendix B.2.

The production function of the human capital, $f(h_j, s_j, a)$, depends on the agent's human capital, h_j, time put into human capital production, $s_j \geq 0$ and learning ability, a. The human capital production function is given by $f(h, s, a) = a(hs)^\alpha$ with $\alpha \in (0, 1)$.[7] I assume that human capital accumulation technology is the same during the schooling (college) and the on-the-job training periods.[8]

Even though the production function of human capital for the three distinct career paths is in the same form, they differ in the human capital depreciation rates, δ^i, and the growth rate of the skill prices, g^i, estimated using the PSID data survey years 1968-2019. As explained in Section 2.5 in the previous chapter, Skill-Biased Technical Change (SBTC), as a shift in the production technology, favours skilled (for example, more educated) labour over unskilled labour by increasing its relative productivity, demand, and skill prices. Based on SBTC, a college education can provide students with higher-demand skill sets. STEM provides these skill sets more than other majors. Therefore, the skill price of STEM-type

[7]The functional form of human capital accumulation employed in this study is extensively utilized in the literature on human capital accumulation. The original functional form, as introduced in the seminal work by Ben-Porath (1967), includes an additional term for the input of goods. However, for the sake of simplicity, this term is omitted, as elucidated in the section entitled "Ben-Porath model in discrete-time."

[8]Similar to the assumptions made by Ionescu (2009), Ionescu (2011), Manuelli and Seshadri (2014), and Athreya et al. (2019).

human capital is expected to be more valued in the labour market than ARTS and high school graduates. An obvious implication of the different skill prices is to generate various earnings streams.

3.2.4 Earnings

At each age j, for an individual in educational track $i \in \{ST, AT, NC\}$, labour income is given by $w_j^i h_j^i n_j$. The rental rate of human capital or skill price, normalized to one in the first model period ($w_1^i = 1$), and evolve according to $w_{j+1}^i = w_j^i(1 + g^i)$.[9] The growth rate of skill prices, g^i, are constant over time and specific to the schooling choice i. h_j^i denotes the quantities of human capital at the beginning of the age j for each career path, i, and $n_j \geq 0$ is the time spent in the market work. The first-period labour income is denoted by $y_1 = w_1 h_1 n_1$. Skill prices are equal to one in the first period. Therefore, all agents receive a wage equal to their initial level of human capital h_1.

3.2.5 Agent's problem: No-college path

The agents' problem is to maximize lifetime utility expressed in Equation (35) subject to a few constraints. Agents face a natural debt limit: each period, they can borrow up to the present value of their lifetime income. This arrangement enforces a no-borrowing restriction only in the final period of their life, that is, $x_{E+1} \geq 0$. Moreover, agents' consumption is always positive and restricted by their earnings net of savings/borrowings,

$$c_j \leq w_j h_j n_j + (1 + r)x_j - x_{j+1} \quad , \; 0 \leq n_j \leq 1 \quad \text{for} \quad j = 1, \ldots, J, \tag{36}$$

$$c_j \leq (1 + r)x_j - x_{j+1} \quad \text{for} \quad j = J + 1, \ldots, E,$$

[9]Similar to Ionescu (2009), I normalized skill prices of all educational tracks in the first period because the job market does not necessarily value students' human capital stocks when they are in the college (Autor et al., 2003). In other words, college students can benefit from the growth in their skill price only after graduation.

$$c_j > 0 \quad \text{for} \quad j = 1, \ldots, E.$$

During working periods, agents accumulate human capital affected by a depreciation rate, δ^{nc},

$$h_{j+1} = h_j(1 - \delta^{nc}) + a(h_j s_j)^{\alpha}, \ \alpha \in (0, 1), \ s_j \geq 0. \tag{37}$$

Agents' skill prices grow at the constant rate, g^{nc},

$$w_{j+1} = w_j(1 + g^{nc}) \quad \text{for} \quad j = 1, \ldots, J.$$

I recast the problem in a dynamic programming framework and solve it backward for all the model choices. In the retirement periods, $j = 9. \ldots, 12$, agents consume and save/borrow at the rate of return on capital, r. The Bellman equation in retirement is

$$V^{NC}(j, h, x, a) = \max_{x'} \Big[\ln((1 + r)x - x') + \beta V^{NC}(j + 1, h', x', a) \Big], \tag{38}$$

$$\text{with} \quad V^{NC}(E + 1, h, x, a) = 0.$$

For the working life, $j = 1. \ldots, 8$, agents' value function is given by

$$\begin{aligned} V^{NC}(j, h, x, a) = \max_{\{s,n,h',x'\}} \Bigg[& \ln(whn + (1 + r)x - x') - \psi \frac{(n + s)^{(1+1/\kappa)}}{1 + 1/\kappa} \\ & + \beta V^{NC}(j + 1, h', x', a) \Bigg], \end{aligned} \tag{39}$$

$$\text{subject to} \quad h' = h(1 - \delta^{nc}) + a(hs)^{\alpha},$$

$$w' = w(1 + g^{nc}),$$

$$s \geq 0, \quad n \geq 0, \quad s + n \leq 1.$$

Solutions to this problem are given by the optimal decision rules for the time spent in the production of the human capital, $s_j^{*NC}(h_1, x_1, a)$, the working time, $n_j^{*NC}(h_1, x_1, a)$, the level of human capital, $h_j^{*NC}(h_1, x_1, a)$, and assets carried to the next period, $x_j^{*NC}(h_1, x_1, a)$, as functions of initial human capital, h_1, initial assets, x_1, and ability, a.

3.2.6 Agent's problem: College paths (STEM or ARTS)

The life cycle of individuals on the college track consists of four consecutive and interconnected phases: college ($j = 1$), work and loan repayment ($j = 2, 3$), work ($j = 4-8$), and retirement ($j = 9 - 12$). While these agents share similarities with the no-college-track individuals in problem formulation, there are key differences in the first three periods ($j = 1 - 3$) for college-track individuals. During the college period ($j = 1$), college-track individuals receive student loans, denoted as $d \in D$. These student loans are considered debts and must be fully repaid during the subsequent work and loan repayment periods ($j = 2, 3$). By the end of the third period, college graduates have successfully paid off their student loans and become debt-free. I write the following Bellman equation for $j = 2, 3$ where $i \in \{STEM, ARTS\}$,

$$
\begin{aligned}
V^i(j, h, x, a) = \max_{\{s,n,h',x'\}} \Bigg[& \ln(whn + (1 + r)x - x' - p) \\
& -\psi \frac{(n + s)^{(1+1/\kappa)}}{1 + 1/\kappa} + \beta V^i(j + 1, h', x', a) \Bigg],
\end{aligned}
$$

$$
\begin{aligned}
\text{subject to} \quad & h' = h(1 - \delta^i) + a(hs)^\alpha, \\
& w' = w(1 + g^i), \\
& d' = (d - p)(1 + r_s), \\
& s \geq 0, \quad n \geq 0, \quad s + n \leq 1.
\end{aligned}
$$

In these repayment periods, agents pay p, which represents a fixed payment based on their college loan amount, d, and the interest rate on student loans, r_s.[10] The interest rate on student loans is deterministic and fixed by the government. The repayment schedule is defined as $p_j = d_j / (\sum_{t=0}^{T-1} \frac{1}{(1+r_s)^t})$ where T represents the numbers of repayments remained including that of age j.[11] Individuals repay the loan in two model periods equivalent to ten

[10] College students do not pay interest on the loan when they are still in college, that is, $j = 1$.
[11] $T = 2$ when $j = 2$ and $T = 1$ when $j = 3$.

years as in the standard consolidation plan, similar to Ionescu (2011), Ionescu and Simpson (2016), and Athreya et al. (2019).

To pay the college tuition and fees, tf, in the first period ($j = 1$), college students can work while studying and earn $w_1 h_1 n$, where h_1 is their initial stock of human capital and w_1 represents their initial human capital rental rate, set to one. In addition to the earnings obtained from working, students may use their initial assets, x, need-based student loans, $d(x)$, need-based grants, $G(x)$, and merit-based grants or scholarships, $S(a)$. Need-based aid decreases with initial assets, and scholarships increase with the agent's ability. The following Bellman equation is for the college period, $j = 1$. In this case, I use the first year of the repayment period, $j = 2$, as the terminal node for the college period,

$$V^i(1, h, x, a) = \max_{\{s,n,h',x'\}} \Bigg[\ln(whn + (1 + r)x - x' - tf + d(x) + G(x) + S(a)) - \psi \frac{(n + s)^{(1+1/\kappa)}}{1 + 1/\kappa} + \beta V^i(2, h', x', a) \Bigg],$$

$$\text{subject to} \quad h' = h(1 - \delta^i) + a(hs)^\alpha,$$

$$w' = w(1 + g^i),$$

$$d(x) = \min\{d_{\max}, \max(COA - x - G(x), 0)\},$$

$$s \geq \xi, \quad h' \geq \theta^i h,$$

$$n \geq 0, \quad s + n \leq 1,$$

$$x' \geq 0.$$

Agents are eligible to borrow up to the "unmet need," $d(x) = COA - x - G(x)$, defined as the total college cost, COA (Cost Of Attendance), less the initial asset and need-based grant aid, $G(x)$ (Denning et al., 2019).[12,13] The amount of the student loan, $d(x)$, is constrained by the total loan limit $d_{\max}$, set by the government.

In my model, agents can work during college studies but cannot fully allocate their time to work. In other words, students must invest at least a fraction of their time endowment, ξ, in studying. There are two reasons to assign a lower bound for the time investment in college. First, it is a threshold for the minimum required time to study, pass the courses, and graduate. Second, it reduces the risk that agents in the model devote their time entirely to work and can still graduate from college with no study time. Without this commitment, the model college students with a high level of ability and initial human capital can fully work in the market during college with no time investment. After five years, they will graduate from college without studying but receiving the benefits of scholarships, grants and loans - which is impossible in real life. Another proxy for graduation is the minimum human capital required to accumulate during collge, $h' \geq \theta^i h$, which is explained in the calibration part, Section 3.3, titled as A proxy for accumulating credits required to graduate.

Optimal decision rules give solutions to agents' problems: the next period's choices of optimal human capital, $h_j^{*i}(h_1, x_1, a)$, the next period's assets, $x_j^{*i}(h_1, x_1, a)$, the time devoted to accumulating human capital, $s_j^{*i}(h_1, x_1, a)$, and the working time, $n_j^{*i}(h_1, x_1, a)$, all as functions of initial human capital, h_1, initial assets, x_1, and ability, a.

3.2.7 College enrollment in fields of STEM or ARTS

The choices from the initial state $(1, h, x, a)$ of an agent are as follows

[12]Cost of Attendance could consist of tuition and fees, the cost of room and board, the cost of books, supplies, transportation, and miscellaneous expenses such as a reasonable cost of a personal computer. Source: Office of Federal Student Aid, "Wondering how the amount of your federal student aid is determined?", (last accessed December 2023).

[13]The government measures the initial asset (x) of students using the Expected Family Contribution (EFC) formula. The EFC calculation is based on students' Free Application for Federal Student Aid (FAFSA) information about their parents' income and wealth. EFC determines students' eligibility for certain federal student aid types. Source: Office of Federal Student Aid, 2021-2022 Expected Family Contribution (EFC) Formula Guide, (last accessed December 2023).

- STEM if $V^{ST}(1,h,x,a) > V^{AT}(1,h,x,a)$, and $V^{ST}(1,h,x,a) > V^{NC}(1,h,x,a)$,
- ARTS if $V^{AT}(1,h,x,a) \geq V^{ST}(1,h,x,a)$, and $V^{AT}(1,h,x,a) > V^{NC}(1,h,x,a)$,
- No-college if $V^{NC}(1,h,x,a) \geq V^{ST}(1,h,x,a)$, and $V^{NC}(1,h,x,a) \geq V^{AT}(1,h,x,a)$,

where $V^{ST}(1,h,x,a)$, $V^{AT}(1,h,x,a)$, and $V^{NC}(1,h,x,a)$ are the maximum present values of an agent's lifetime utility if they choose STEM, ARTS or no-college paths, respectively.

3.3 Mapping the model to the data

The findings of this dissertation are based on three sets of parameter values. The first set of parameters is standard in the literature, such as the curvature parameter of the human capital production function, the risk-free interest rate, and the discount factor. The second set contains the parameters calibrated directly to the data, such as student loan limit, the direct cost of college (tuition and fees), interest rates on student loans, skill prices, human capital depreciation, and governmental aids. Table 3.2 shows the first two sets required to solve the model. The model parameters capture the behaviour of individuals who enrolled in college in 2014; therefore, the monetary values of these parameters are given in 2014 dollars.

Table 3.3 depicts the third set of parameters related to the joint distribution of initial endowments of the model economy used to simulate the model economy (ability, initial human capital, and initial assets). To calibrate these parameters, I use several observable implications of the model and jointly estimate the parameters I do not observe in the data by minimizing the gap between model moments and those of the data.

Real interest rate. I set the real interest rate equal to 4%. Like most macroeconomic models, there is only one asset in my model. Usually, scholars take the return on this asset as an average of two returns: the risk-free return (about 1%) and the (after-tax) return to capital (around 7-8%).[14]

[14] For a long-run average of the risk-free return, see the 10-Year Treasury Inflation-Indexed Security (TIIS)

Discount factor. For most macroeconomic models, the real interest rate pins down the value of the discount factor. However, in a life cycle model, there is no tight connection between the real interest rate and the discount factor (Ríos-Rull, 1996). The literature on the standard life cycle models shows an excessive variability in the estimates of the discount factor, β, from around 0.94 to almost one. For example, Iacoviello and Pavan (2013) use two classes of households, an "impatient" group with a discount factor of 0.941 (two-thirds of the population) and a "patient" group with a discount factor of 0.999 (one-third of the population). Also, for the sensitivity analysis, they present the results for an alternative calibration for a homogeneous single discount factor equal to 0.978. In another life cycle model, Hendricks (2007) studies the role of discount rate heterogeneity in understanding wealth inequality in the U.S. economy. Using the PSID dataset, the author estimates the range of discount rates between 0.935 to 0.962. Also, Abbott, Gallipoli, Meghir, and Violante (2019) build a life-cycle model with endogenous labour supply, consumption, saving and education choices. They set the time discount factor equal to 0.9753. Furthermore, in a recent paper, Wu (2021) uses 0.99 as the discount factor in an overlapping generations incomplete-market life-cycle model with heterogeneous agents. Considering the existing range of the discount factor in the life cycle model literature, I set this parameter equal to 0.98.[15]

rate in FRED:
Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Inflation-Indexed (DFII5),
Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Inflation-Indexed (DFII10),
Market Yield on U.S. Treasury Securities at 20-Year Constant Maturity, Inflation-Indexed (DFII20),
and for the example of the long-run return to capital, see S&P 500 Average Return, (last accessed December 2023).

[15]See more about discount rate heterogeneity in Browning and Lusardi (1996), Frederick, Loewenstein, and O'Donoghue (2002), and De Nardi and Fella (2017).

Table 3.2: Parameter values

Parameter	Name	Value	Target/Source
r	Annual real interest rate †	4%	Average of risk-free and capital returns
β	Annual discount factor †	0.98	Literature on the life cycle models
ψ	Disutility from work or investing in human capital	12.4	Badel et al. (2020)
κ	Frisch elasticity	0.614	Badel et al. (2020)
r_s	Annual student loan real interest rate †	3%	Long-run average (1980-2020)
g^{ST}, g^{AT}, g^{NC}	Human capital annual rental growth rates †	0.53%, 0.35%, -0.13%	PSID (survey years 1968-2019)
δ^{ST}, δ^{AT}, δ^{NC}	Human capital annual depreciation rates †	0.9%, 0.6%, 0.0%	PSID (survey years 1968-2019)
α	Production function elasticity	0.80	Guvenen and Kuruscu (2010)
COA	Cost Of Attendance (full college cost)	\$135,000*	NCES, Digest of Education Statistics 2020
tf	Tuition and fees	\$64,000*	NCES, Digest of Education Statistics 2020
d_{max}	Government limit on student loan	\$31,000*	NCES **
ξ	Minimum study time in college	0.25	Abbott et al. (2019)

† In the model, all annual rates will be transformed into the five-year model period rates.

* In 2014 constant dollars.

** NCES ≡ National Center for Education Statistics.

ST ≡ STEM, AT ≡ ARTS, NC ≡ No-college.

Interest rate on college loans. My model uses the standard repayment plan and abstracts from modelling other repayment options.[16] In the standard loan repayment plan, individuals repay the loan in equal monthly payments for the life of the loan, up to ten years. By setting one model period to five years, the timing will also be consistent with the ten years of loan repayment, equal to two model periods after graduation.

I computed the college loan interest rate based on two methods used in the literature. The first method is to set the interest rate based on the long-run average of the interest rate (for example, see, Ionescu, 2011). Using this method, I calculated the real interest rate on college loans based on the long-run average of fixed interest rates for Direct Loans and Federal Stafford Loans for undergraduate borrowers entering college between 1980-81 and 2018-19. This calculation leads to 3.08%.[17,18,19] The second method is to consider the interest rate at the time of entry or during the academic years on which the model is calibrated (for example, see, Athreya et al., 2019; Ionescu & Ionescu, 2014; Ionescu & Simpson, 2016). Following this approach, I consider the same real interest rate for the students who entered college in 2014-15, equal to 2.91%. Using both approaches, I use the average real interest rate, 3%.

Curvature parameter of the human capital production function. Browning, Hansen, and Heckman (1999) report a diverse parameter estimate for the curvature parameter of the human capital production function, α, between 0.5 to 0.9. Estimates of α are generally around 0.8 and higher, even close to 1, representing a near linear technology for human capital accumulation function. For example, Heckman (1976) delivers a point estimate of 0.812, Heckman et al. (1998) reports from 0.832 to 0.945. the range of estimates for Christopher

[16]For information on various student loan repayment plans and their conditions and eligibility criteria, see Federal Student Aid, Student Loan Repayment, Repayment Plans, (last accessed December 2023).

[17]Source: Office of Federal Student Aid, Understand how interest is calculated and what fees are associated with your federal student loan, section: "Fixed Interest Rates for Direct Subsidized Loans and Subsidized Federal Stafford Loans - Undergraduate Borrowers" (last accessed December 2023).

[18]Extra sources for student loans are available at Historical Federal Student Loan Interest Rates and Fees, and Economics of Guaranteed Student Loans, (last accessed December 2023).

[19]To make the nominal interest rates real, I calculate the long-run average for the Consumer Price Index for All Urban Consumers. Source: Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in the U.S. City Average, Percent Change from Year Ago, Monthly, Seasonally Adjusted, (last accessed December 2023).

(2002) is from 0.942 to 1.00. Guvenen and Kuruscu (2006, 2010) set the curvature of the human capital accumulation to 0.8. I set α to 0.8, a value equal to the lower end of this empirically reasonable range.[20]

Cost of attendance (COA). The total cost of college is the average undergraduate tuition and fees and room and board rates charged for full-time students in degree-granting postsecondary institutions.[21] In the model, the COA is a parameter that influences the eligible amount of the student loan, $d(x_1) = \min\{d_{\max}, \max(COA - x_1 - G(x_1), 0)\}$, where $d_{\max}$, set by the government, is the cumulative borrowing limits for federal loans to (dependent) students equal to \$31,000 in the year 2014.[22]

I derived COA as the enrollment-weighted average of the total cost at a public four-year institution (\$96,000) and a private four-year institution (\$202,000) between the academic years 2014-15 and 2018-19, weighted by the fraction of students attending each in the data (63 and 37 percent, respectively). This weighted average delivers a total college cost (COA) equal to 135,000 in 2014 dollars for which the data are taken from the U.S. Department of Education, National Center for Education Statistics (NCES), Digest of Education Studies 2019 (Tables 330.10 and 303.25).

Average direct costs or tuition and fees, tf. Total tuition and fees are based on 120 credits of four-year college studies.[23] This figure is the enrollment-weighted average of the tuition and fees at a public four-year institution (\$35,000) and a private four-year institution (\$113,000) between the academic years 2014-15 and 2017-18, weighted by the fraction of students attending each in the data, 63% and 37%, respectively. I set the average direct cost of college to $tf = 64{,}000$ in 2014 dollars, that is, the average undergraduate tuition and fees for full-time students in degree-granting postsecondary institutions for the years 2014-15 through 2017-18 (NCES, Tables 330.10 and 303.25.)

[20] I vary this parameter, and a 0.8 value best fits the data I used. Higher values deliver more steeped age-earnings profiles, especially for higher-ability STEM students.

[21] See What does cost of attendance (COA) mean?, (last accessed December 2023).

[22] Source: The U.S. Department of Education offers low-interest loans to eligible students to help cover the cost of college or career school., (last accessed December 2023).

[23] See What is a Credit Hour & How Tuition Fees are Calculated from The Credit Hour?, (last accessed December 2023).

Merit-based scholarship, $S(a)$. Ionescu (2009) introduces a distribution for merit-based financial aid that increases with ability. However, not any specific function for this increase in merit-based scholarships is provided in her paper. I derived the merit-based grant grid point values from her paper's Matlab codes and plotted them as shown in Figure 3.2. The horizontal axis of this figure represents the range of ability of high school graduates. The graph's vertical axis is transformed into 2014 dollars, consistent with my model. This figure shows that only a small group of the lower-ability agents do not receive this type of grant, and most high-ability students receive the highest level of grants.

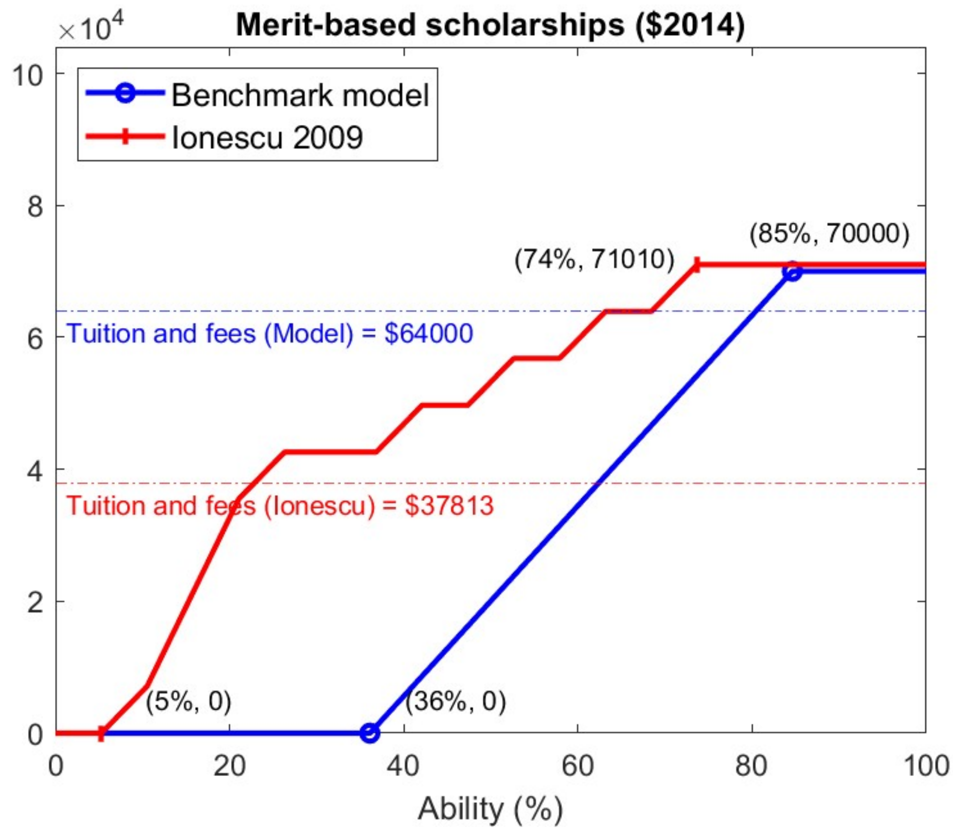

Figure 3.2: Merit-based scholarship distributions of the benchmark model and Ionescu (2009)

Inspired by this distribution, I defined a simple, functional form for this type of financial aid as depicted in Figure 3.2. I used the GPA of high school graduates as a proxy for learning ability. In this figure, the zero-ability point corresponds to the lowest Grade Point Average (GPA) score required to graduate from high school, GPA =1. The highest ability level represents the highest GPA, equal to four. The merit-based scholarships start with zero amount at 36% of ability close to the minimum level of high school GPA accepted by universities (GPA=2).[24,25] Then, the scholarships linearly increase with a maximum amount of $70,000 given to individuals with 85% and higher abilities close to the GPA=3.5 threshold under which some colleges and universities provide a full scholarship covering tuition and fees and some parts of the total cost of attendance.[26,27]

Need-based grant, $G(x)$. Ionescu (2009) does not provide this type of financial aid. I extend the author's model and offer need-based financial assistance, common among colleges and universities, such as Pell Grant and other state financial aid programs. Following the same technique to set the merit-based scholarship, the need-based grant is a decreasing function of the initial asset, as shown in Figure 3.3. In my model, the total grant for four-year college students starts from around $70,000 for the zero initial-asset students to cover their tuition and fees.[28] The grant then linearly decreases and reaches zero for those who have around $47,000 in their initial asset. Those whose initial assets exceed this threshold do not receive the need-based grants.

Minimum study time, ξ. My model does not have the risk elements, such as the uncertainties associated with college graduation. As a result, I am not modelling college dropouts. Nevertheless, the model does incorporate a stipulated minimum threshold to study during college to ensure graduation. The lower bound of the fraction of time to study for college students is set to one-fourth of the time endowments of college students, that is, $\xi = 0.25$. Calibrating the minimum study time is based on taking 10-12 credits, on average, each semester. As a result, on average, agents need 10-12 hours of in-class study and around 20-30 hours of extra activities such as hours spent studying, reading, writing, doing homework or lab work, analyzing data, rehearsing, and other academic activities in

[24] (2-1)/(4-1)*100=33.33 percent

[25] For colleges and universities that accept high school graduates see 2.0 GPA Colleges: Browse Schools That Accept a 2.0 GPA and Universities Accepting Low GPA: List of Graduate Schools with Low GPA Requirements, as examples, (last accessed December 2023).

[26] (3.5-1)/(4-1)*100=83.33 percent

[27] Examples are Florida Academic Scholars (FAS), Florida State Benacquisto Scholarship Program, and Columbia College Scholarship, (last accessed December 2023).

[28] Based on Trends in college pricing. CollegeBoard 2015, students in public four-year institutions who receive enough grant aid to cover their entire tuition and fees are from families with low yearly incomes below $30,000 (last accessed December 2023).

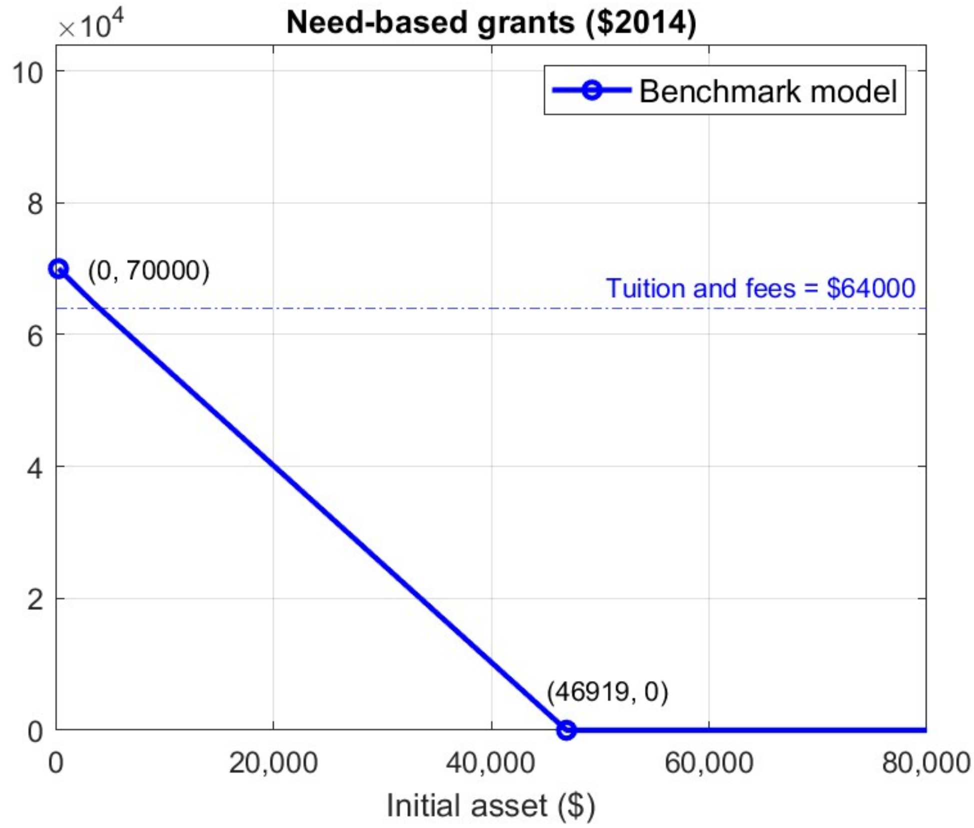

Figure 3.3: Need-based grant as a function of initial asset

a typical 7-day week of 168 hours in total. This calculation is based on a general rule of thumb: for each class, students should spend approximately 2-3 hours of study time for each hour they spend in class. Some scholars put the study time of college students as a fixed parameter. For example, the model economy in Abbott et al. (2019) requires students to study for 25% of their time endowment. In their paper, the study time is a fixed parameter. It is not a choice of agents. But in my model, respecting ξ as the minimum threshold, agents can choose their study and working times based on maximizing their lifetime utility problem.[29]

A proxy for accumulating credits required to graduate. My model is based on Ionescu (2009), which does not have the college dropout decision of agents. To make the model closer to the "college completion" setup, I introduced a minimum increase in human

[29] Also see New Research Shows that Today's College Students Are Studying Less, and Is Your College Student Investing Enough Time Studying? (last accessed December 2023).

capital during college as a proxy for passing the necessary credits, $h' \geq \theta^i h$. This approach defines thresholds as specific "percentage increases" of initial human capital during college. I experimented with different percentages and determined that incorporating a 20% increase in human capital during college for STEM ($\theta^{STEM} = 1.2$) and a 10% increase for ARTS ($\theta^{ARTS} = 1.1$) at each initial human capital level produces the optimal fit for the model when aligning it with the data. This approach associates "college graduation" directly with learning ability. Together with the existing parameter (the minimum college study time, $\xi = 0.25$), these conditions relate graduation to both "learning ability" and the required effort (time to study) to graduate.

3.4 Computation

To some extent, the computation procedure is similar to that used in Ionescu (2009). I solve the optimal decision rules for investing time in human capital accumulation, working in the labour market, savings, and the following period level of human capital.

Computation algorithm

To calculate the optimal decision rules, I search for the solutions over the grid using backward induction on the value function. In this regard, I construct grids for learning ability $a \in (0, \bar{a}]$, human capital $h \in (0, \bar{h}]$, assets $x \in (0, \bar{x}]$, time investing in human capital $s \in [0, 1]$, working time $n \in [0, 1]$, student loan $d \in [0, \bar{d}]$ consisting of 20, 40, 20, 15, 15, and 20 grid points, respectively. The algorithms for the no-college path and the college paths (STEM, ARTS) have much in common; however, they differ in some aspects, which I explain here in detail.

Optimal decision rules for time allocation, assets, and human capital

No-college path: I break the whole life cycle into two stages: retirement periods, $j = 9, \ldots, 12$, and working ages $j = 1, \ldots, 8$. These stages are different in the choices agents must decide on. For each retired agent, starting from the last age, $E = 12$, given current assets, I evaluate the remaining lifetime utility for each value of the following period assets in the grid. Then, I choose the one that maximizes the remaining lifetime utility at each age, j.

During work periods, from the last age of working life, $J = 8$, backwards, I evaluate the remaining lifetime utility for each value of savings, time to invest in human capital, and time to work. Since the human capital values of the following age, $h' = h(1 - \delta^{nc}) + a(hs^{\alpha})$, may not lie at a grid point, I linearly interpolate the following period value functions. Then choose the combination of the investment time, working time, and the subsequent period assets that maximize the lifetime utility at each age. This process finally delivers the lifetime utility values for all combinations of initial human capital, h_1, initial asset, x_1 and ability, a, in the first period, $j = 1$. Finally, agents will use these first-period value functions to decide their educational paths.

After solving the model, given the optimal decisions and tracing the choices, I compute the stream of lifetime earnings, savings, consumption, human capital, working, and hours invested in human capital for all agents if they choose the no-college path.

College paths (STEM/ARTS): Introducing debt and repayment of student loans makes the problem more complicated. Therefore, I divide the life cycle into four stages: retirement periods, $j = 9, \ldots, 12$, post-payment periods, $j = 4, \ldots, 8$ in which no debt to be paid, repayment periods, $j = 2, 3$, and the college period, $j = 1$. The first age in each stage will be the terminal node of the previous step to connect all stages. For example, $j = 9$ will be the terminal node for the post-payment stage. Treating retirement and working periods (post-payment and repayment) is similar to those in the no-college path. However, repayments of total student loans create an evolution of debt in the repayment period, $d' = (d - p)(1 + r_s)$. Like the human capital function, the next age debt level, d', may fall off the debt grid points. Therefore, finding the position of the subsequent debt level on the grid line is required to implement linear interpolation..

After solving the model for STEM and ARTS paths, similar to the no-college path, I compute the stream of lifetime earnings, wages, savings, consumption, human capital, working time, and hours invested in human capital for all combinations in the initial state space (h_1, x_1, a). Finally, I compare the first-year value function of three educational paths (no-college, STEM, and ARTS) to determine the optimal college enrollment decisions for all agents in the state space at age $j = 1$.

3.5 Simulation

To simulate the economy, first, it is required to determine the distribution of initial endowments in the benchmark model economy. I follow Athreya et al. (2019) and restrict the initial distribution to lie on a three-dimensional grid in the space of learning ability, initial human capital, and initial asset $(A \times H \times X)$ to be jointly, log-normally distributed. The distribution of initial characteristics (ability, human capital, and assets) of high school graduates is determined by nine parameters, $\boldsymbol{\gamma = (\mu_a, \sigma_a, \mu_h, \sigma_h, \mu_x, \sigma_x, \rho_{\mathrm{ah}}, \rho_{\mathrm{ax}}, \rho_{\mathrm{hx}})}$, including the mean and standard deviation of abilities (μ_a, σ_a), initial human capitals (μ_h, σ_h), initial assets (μ_x, σ_x), and the three cross-correlations between initial endowments $(\rho_{\mathrm{ah}}, \rho_{\mathrm{ax}}, \rho_{\mathrm{hx}})$.

I apply the Simulated Annealing algorithm in MATLAB to fit these nine distributional parameters of the initial economy. Providing all initial guesses for the parameters of interest, I search over the vector of parameters that minimizes the distance between the model and the data by solving the following problem

$$min_\gamma \Bigg\{ \overbrace{\Bigg(\sum_{j=2}^{8} \Big| log\Big(m_j / m_j(\gamma)\Big)\Big|^2 + \Big| log\Big(g_j / g_j(\gamma)\Big)\Big|^2 + \Big| log\Big(d_j / d_j(\gamma)\Big)\Big|^2 \Bigg)}^{\text{First part}} + \underbrace{\Big| \Big(\eta_1 - \eta_1(\gamma)\Big)\Big| + \Big| \Big(\eta_2 - \eta_2(\gamma)\Big)\Big|}_{\text{Second part}} \Bigg\}. \tag{40}$$

As Equation (40) shows, the vector of parameters, $\gamma = (\mu_a, \sigma_a, \mu_h, \sigma_h, \rho_{\mathrm{ah}}, \rho_{\mathrm{ax}}, \rho_{\mathrm{hx}})$, are estimated jointly by minimizing the distance between 23 moments of the PSID data (1967-2018) and the model. The first part shows the key moments of three statistics of the life cycle income distribution (mean, Gini, and the mean/median ratio) of seven working periods ($3 \times 7 = 21$ moments).[30] The second part includes two moments representing the enrollment rates of STEM and ARTS, (η_1, η_2).

To minimize the sum of terms inside the Equation (40), first, I simulate the model economy for the initial values of the model economy initial distribution parameters (γ). Second, calculate three sets of statistics for all seven working ages, j, in the model, that is, mean, $m_j(\gamma)$, Gini, $g_j(\gamma)$, and mean/median, $d_j(\gamma)$, for the first part of the equation. I also calculate the enrollment rates, $(\eta_1(\gamma), \eta_2(\gamma))$. Then, calculate the log difference of model statistics with the corresponding ones constructed from the PSID data on earnings: mean (m_j), Gini (g_j), and mean/median (d_j). Similarly, calculate the difference between the graduation rates of the model and those of the PSID sample data used to calibrate the model. Table 3.3 shows the results given by this algorithm which provide the best possible outcome and fitness based on the complexity level of the model at hand.

Table 3.3 provides positive cross-correlations among initial endowments, which aligns with findings of other scholars.[31] In Table 3.3, the correlation between learning ability and initial asset, ρ_{ax}, is the highest among three positive cross-correlations among initial endowments.[32] Belley and Lochner (2007) show that 70 percent of high-ability young people are from the top half of the family income distribution in the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97).[33] Family inputs such as parental time, home

[30]Example of scholars who estimate structural parameters by minimizing the distance between an empirical age profile and a model age profile are Huggett et al. (2006), Ionescu (2009, 2011), and Athreya et al. (2019). Some other examples are DeNardi, French, and Jones (2010), who study health expenses and saving among the elderly, and Huggett et al. (2011), Kaplan (2012), Aguiar and Hurst (2013), who study the life cycle consumption and inequality.

[31]Examples are Ionescu (2009, 2011), Athreya et al. (2019), Ionescu and Simpson (2010), Huggett et al. (2006, 2011), Blandin (2018)

[32]The interpretation of the coefficient varies depending on the subject under investigation. When examining phenomena that are challenging to quantify, it is reasonable to anticipate lower correlation coefficients. Within this type of data analysis, correlations above 0.4 are generally regarded as relatively strong, while correlations ranging from 0.2 to 0.4 are considered moderate. Correlations below 0.2 are typically deemed weak in these circumstances. Source: Correlation In Statistics: Meaning, Types, Examples & Coefficient (last accessed December 2023).

[33]Table 2 in Belley and Lochner (2007) represents the joint distribution of family income and AFQT (as

environments, reading books, and the quality of living in good neighbourhoods and schools significantly affect children's abilities and achievements. Dahl and Lochner (2017, 2012) investigate the effect of family income on child development and their instrumental variable (IV) estimates show a significant positive impact of family income on a child's math and reading achievement.[34] The elevated correlation between learning ability and initial asset, denoted as ρ_{ax}, has a notable impact on the initial distribution of the benchmark economy. This influence is manifested in an increased percentage of college students in the highest quartile of initial assets, as outlined in Table 3.5.

Table 3.3: Fitted parameters of the joint log distribution of initial endowments

Parameters	Values
μ_a	0.301
σ_a	0.853
μ_h	5.345
σ_h	0.665
μ_x	3.849
σ_x	1.222
ρ_{ah}	0.152
ρ_{ax}	0.406
ρ_{xh}	0.200

3.6 Model vs. Data

This section presents the model predictions for targeted data moments for the baseline economy.

a proxy for ability) quartiles across both cohorts 1979 and 1997. These distributions show a strong positive correlation. The table reveals that the quartiles three and four of family income together constitute around 70% of quartile four of the AFQT (For example, for NLSY79: (10.09+7.20)/(10.09+7.20+5.38+2.37) $\approx$ 70%).

[34]The estimates imply that a $1,000 increase in income raises combined math and reading test scores by about 6 percent of a standard deviation.

Targeted Moments. Figure 3.4 shows the life cycle statistics (Mean, Mean/Median, and Gini) of earnings profiles for the whole population. The data plots of mean earnings look somewhat different than those in Figure 2.1 because they are based on the seven model periods adjusted to 35 years of working age (25-59).

Table 3.4 shows the college student graduation rates by field of studies. The table shows that the model predicts 17.0% and 6.3% of total high school individuals graduate in STEM and ARTS compared to 16.6% and 6.5% in the sample data.

Table 3.4: Data versus model for targeted moments

Moments	Model (%)	Data (%)[1]
Total graduation rate[2] (STEM and ARTS)[3]	23.3	23.1
STEM graduation rate	17.0	16.6
ARTS graduation rate	6.3	6.5

[1] Data sample is from the PSID dataset, 1968-2019 survey years, as explained in Chapter 2.

[2] In the model, the graduation rate and the enrollment rate are identical because whoever enrolls will graduate.

[3] Total graduation rate is the sum of those of STEM and ARTS in the sample. It does not represent other college majors such as Finance, Management, Sports, and Law.

Figure 3.4 and Table 3.4 show that the model fits the moments of interest relatively well. To bring the model close to data, I use Equation (41) as a measure of goodness of fit,

$$\frac{1}{3(J-1)+2}\left\{ \overbrace{\left(\sum_{j=2}^{J} \left| log\Big(m_j/m_j(\gamma)\Big) \right| + \left| log\Big(g_j/g_j(\gamma)\Big) \right| + \left| log\Big(d_j/d_j(\gamma)\Big) \right| \right)}^{\text{First part}} + \underbrace{\left| \Big(\eta_1 - \eta_1(\gamma)\Big) \right| + \left| \Big(\eta_2 - \eta_2(\gamma)\Big) \right|}_{\text{Second part}} \right\}. \tag{41}$$

The first part of this equation is taken from Huggett et al. (2006), Ionescu (2009, 2011), and Athreya et al. (2019). This part first calculates the (percentage) deviation, in absolute terms, between the model-implied earnings statistics (Mean, Gini, and Mean/Median) and those of data for the whole sample, $\Big(\Big| \ln \Big(\text{data statistics}_j/\text{model statistics}_j\Big) \Big| \Big)$. These

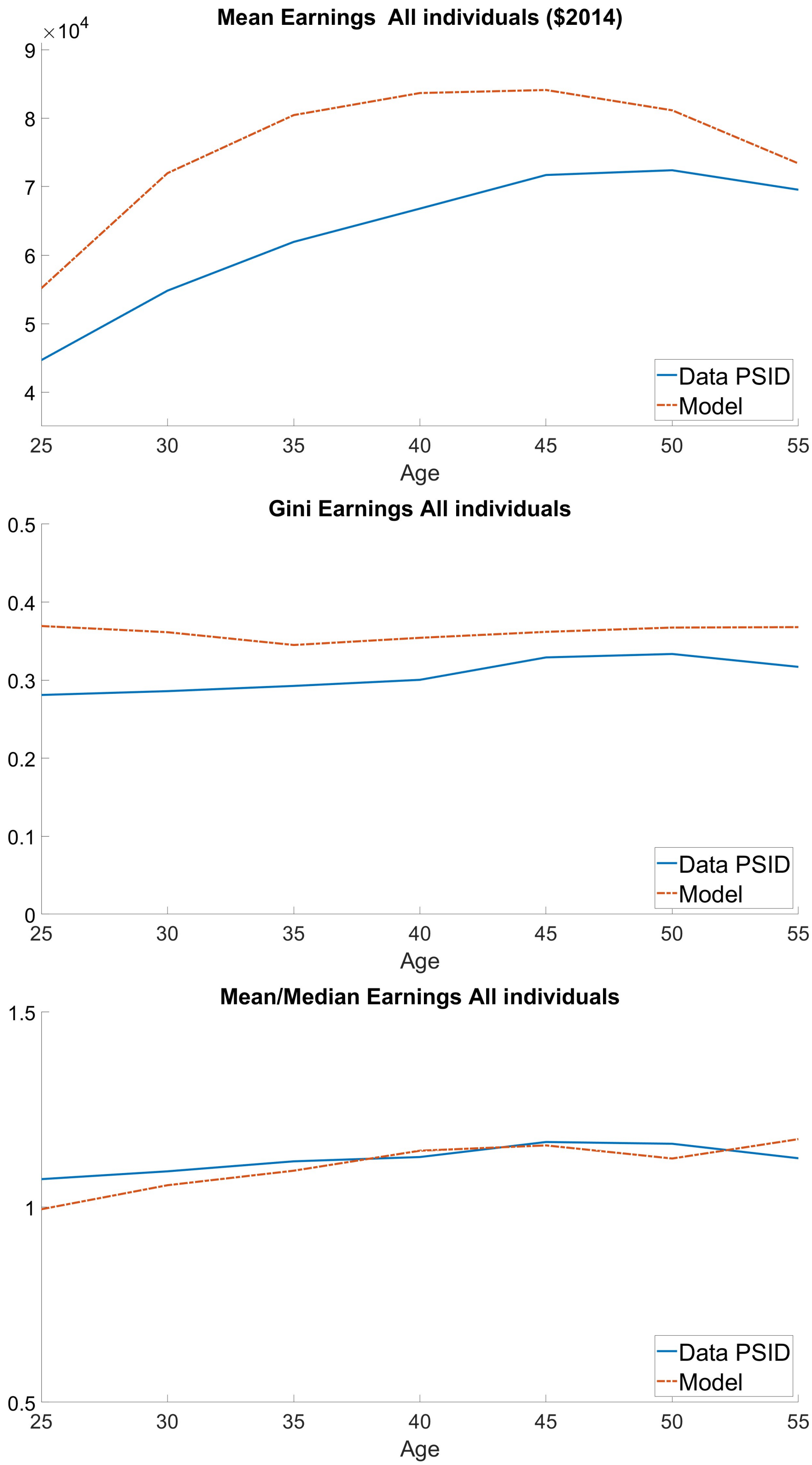

Figure 3.4: Life cycle statistics (Model vs. data)

deviations are calculated for each age starting right after graduation, $j = 2$, until the last year of working age, $J = 8$. Then Equation (41) takes the average of these deviations over all three statistics and seven periods, $3(J - 1)$. The second part represents the (percentage) deviation, in absolute terms, between the STEM and ARTS graduation rates derived from the model and those of the dataset.

My model obtained a fit of 11.8% (where zero percent represents a perfect fit where the moments of the model have no deviations from those in the data). This figure represents reasonable goodness of fit, especially when the depth and complexity of my model are considered. Huggett et al. (2006) find a measure of the goodness of fit between 5.0% to 7.5%. Ionescu (2009, 2011) obtain a fit of 5.3% and 9.8%, respectively, Athreya et al. (2019) obtains a fit of 8%, and Neelakantan, Vidangos, Ionescu, and Athreya (2016) find an 11% goodness of fit.

3.7 Results of the benchmark economy

This section consists of three parts. The first part focuses on career choices, their determinants, and the decision rules. Part two revolves around the results obtained by mapping the model to real-world data and conducting simulations within the benchmark economy. The primary focus of this part is to illustrate the life cycle behaviour of agents within this simulated economy. In the third, I discuss the implications of counterfactual career decisions for the no-college path and provide the relevant figures to demonstrate how consumption, working time, and time allocated for investment would have changed if these individuals had selected different careers than those chosen under the benchmark economy.

3.7.1 Career choices

In this section, I begin by presenting the Euler Equations that have been derived from the model's solution. These equations lay the foundation for establishing decision rules about savings, labour allocation, and investments in human capital. Following this, I delve into a discussion regarding the influence of initial endowments on the decision-making process concerning educational career choices.

3.7.1.1 Decision rules for savings, time to work, and time to invest in human capital (Euler equations)

Following, I present three Euler Equations (42) to (44) and elaborate on the marginal costs and benefits associated with agents' decisions on savings, time to work, and time to invest in human capital. These equations are derived by solving the agents' lifetime value function, considering their preferences, budget constraint, and human capital accumulation function as illustrated in Equations (35) to (37).

Understanding these Euler Equations is crucial for comprehending the foundational elements that shape the life cycle behaviours of agents in the simulated economy. This section clarifies the decision-making processes influenced by the marginal benefits and costs inherent in these Euler Equations. Consequently, these equations will illuminate how marginal benefits and costs shape individuals' decisions throughout the life cycle, encompassing aspects such as consumption, the timing of investment in human capital accumulation, time devoted to work, and savings. I will apply these equations in Section 3.7.2 (Life cycle behaviours of agents in the simulated economy). Also, the concept of these Euler Equations is essential to understand the decisions of individuals in the counterfactual situations as explained in Section 3.7.3 (Counterfactual scenarios).

Working time. Equation (42) governs the decision of working, denoted as n_j, at age j. The left-hand side of the equation represents the marginal cost of working one more unit of time in age j, while the right-hand side shows the marginal benefit. Suppose the agent deviates from its optimal plan by working more at age j and consuming the additional proceeds. The marginal cost of this deviation is represented by the marginal disutility of work, denoted as $U_3(c_j, s_j, n_j)$. However, by working more, the agent receives extra labour income, given by $w_j h_j$. Since the agent values one unit of consumption by the marginal utility of consumption, denoted as $U_1(c_j, s_j, n_j)$, the marginal benefit can be expressed as $U_1(c_j, s_j, n_j)w_jh_j$. If the agent is optimizing, this deviation cannot yield a gain. Therefore, the marginal cost (MC) must be equal to the marginal benefit (MB),

$$-U_3(c_j, s_j, n_j) = U_1(c_j, s_j, n_j)w_jh_j. \tag{42}$$

Investment time. Equation (43) governs the human capital accumulation and affects the investment time decision, s_j,

$$\begin{aligned}&-U_2(c_j, s_j, n_j)\frac{1}{(\partial h_{j+1}/\partial s_j)} = \\ &\beta\Big\{U_1(c_{j+1}, s_{j+1}, n_{j+1})(w_{j+1}n_{j+1}) - U_2(c_{j+1}, s_{j+1}, n_{j+1})\frac{1}{(\partial h_{j+2}/\partial s_{j+1})}\frac{\partial h_{j+2}}{\partial h_{j+1}}\Big\}.\end{aligned} \tag{43}$$

The left-hand side of Equation (43) represents the marginal cost of investing an additional unit of time in human capital accumulation at age j. To analyze a deviation, let's consider a scenario where the agent increases h_{j+1} by one unit while keeping h_{j+2} unchanged or returning it to its original path at time $j + 2$. From the human capital production function $a(h_js_j)^\alpha + h_j(1 - \delta)$, one can observe that a one unit increase in h_{j+1} requires an increase in investment time, denoted as s_j, by an amount determined by the reciprocal of the derivative $(\partial h_{j+1}/\partial s_j)$. Each unit of investment time is valued by the marginal disutility of time investment, denoted as $U_2(c_j, s_j, n_j)$.

The right-hand side of Equation (43) represents the marginal benefit of the decision described. When there is a one-unit increase in human capital at the following age, h_{j+1}, the agent will receive a reward of $w_{j+1}n_{j+1}$ per unit, each of which will be consumed and valued by the marginal utility of consumption, denoted as $U_1(c_{j+1}, s_{j+1}, n_{j+1})$. Additionally, the return to this extra unit of human capital, h_{j+1}, is given by $\partial h_{j+2}/\partial h_{j+1}$. To produce this additional human capital, an investment time of s_{j+1} is required, which will be reduced by $[1/(\partial h_{j+2}/\partial s_{j+1})][\partial h_{j+2}/\partial h_{j+1}]$ units to keep h_{j+2} unchanged. By reducing this extra investment time at $j + 1$, the agent also benefits from a reduction in the flow of disutility at the rate of $U_2(c_{j+1}, s_{j+1}, n_{j+1})$, which represents the marginal disutility of time investment at the following age. Finally, discounting all the benefits to age j using the discount factor

β converts the right-hand side of the equation into the marginal benefit of this deviation. Like the first Euler Equation, this deviation cannot yield a gain, so the deviation's marginal cost (MC) must equal the marginal benefit (MB). This condition ensures that the agent optimizes their decision-making process by equating the costs and benefits of the deviation: $MC = MB$.

Saving. Euler Equation (44) governs the agents' saving decisions and captures the marginal cost and benefit associated with deviating from the optimal investment plan and adjusting consumption accordingly,

$$U_1(c_j, s_j, n_j) = \beta U_1(c_{j+1}, s_{j+1}, n_{j+1})(1 + r) \tag{44}$$

The left-hand side of Equation (44) represents the marginal cost of deviating from the optimal plan, where an agent invests more at age j and consumes the proceeds in the following age. This deviation requires a reduction in consumption, denoted as c_j, by one unit. Thus, the marginal cost of this deviation is given by $U_1(c_j, s_j, n_j)$, which represents the marginal utility of consumption at age j. By renting out the investment, the agent will receive payment in the form of the return on investment, denoted as $1 + r$. At the following age, the agent consumes this return, which is valued by its marginal utility $U_1(c_{j+1}, s_{j+1}, n_{j+1})$. This return is discounted to age j using the discount factor β. If the agent has optimized their decisions, this deviation cannot yield any additional benefits. Thus, the Euler equation (44) holds with equality, ensuring that the marginal cost of the deviation is equal to the marginal benefit.

3.7.1.2 Initial endowments: determinants of career choices

The solution of the model leads to career choices by model agents that depend on the combination of their ability, initial human capital, and initial assets. In this section, I use various figures and tables to explain the economic forces behind career choices. These choices relate to the agents' preferences for savings, time to work, and time to invest in human capital, which depends on the margins.

Ability

The model and the simulation results highlight the significant influence of learning ability as the most critical determinant of career choice. Simulation of the benchmark economy reveals that low-ability agents opt not to pursue a college education, regardless of their initial human capital or asset endowments, as illustrated in Figure 3.6 and Table 3.5.

Table 3.5: Enrollment percentages by four quartiles of all initial endowments

Enrollments (%)	Endowments	Q1 (%)	Q2 (%)	Q3 (%)	Q4 (%)
	Ability	0.0	1.2	9.7	73.8
College (23.3)[1]	Initial human capital	21.3	22.4	23.1	25.7
	Initial asset	21.6	21.8	20.0	28.6
	Ability	0.0	0.0	0.0	60.5
STEM (17.0)	Initial human capital	13.3	15.5	17.4	20.6
	Initial asset	5.0	10.6	17.7	28.6
	Ability	0.0	1.2	9.7	13.3
ARTS (6.3)	Initial human capital	8.0	6.9	5.7	5.1
	Initial asset	16.6	11.2	2.3	0.0

[1] Total enrollment is the sum of STEM, ARTS and no-college in the sample. It does not represent other college majors such as Finance, Management, Sports, and Law.

Suppose a low-ability agent decides to pursue the college path while investing the same amount of time. In that case, their initial human capital will depreciate faster than not choosing the college path. Consequently, their human capital will grow less over the life cycle than if they had chosen college enrollment. This diminished growth in human capital leads to lower expected wages, earnings, and consumption streams for the agent, even though skill prices might be higher in the college path. Moreover, even if the low-ability agent attempts to compensate for the depreciated human capital by increasing their investment time, they would have to endure the disutility of this additional time investment. As indicated in Equation (35), the overall present value of their lifetime utility would be lower than the scenario of not choosing the college path.

Table 3.5 also demonstrates other important features of the simulated model economy. The percent of people who enroll in college is way higher for the highest-ability quartile, that is, 73.8% of agents in the fourth quartile, Q4, almost three times the college enrollment of the economy (23%). Decomposing college students to STEM and ARTS reveals that STEM agents have a higher share among high-ability individuals. They constitute 60.5% of the highest-ability quartile, more than 3.5 times their share in the economy at 17.0%.

Moreover, Table 3.5 highlights that the enrollment percentage based on initial human capital and initial asset is nearly uniform across the four quartiles, suggesting that these two initial endowments do not play a pivotal role in college attendance. However, the stronger correlation between learning ability and initial asset, denoted as ρ_{ax} and depicted in Table 3.3, contributes to the highest percentage of college students in the top quartile of initial assets. This characteristic underscores the secondary role of parental income in the decision-making process regarding college attendance, where learning ability emerges as the primary determinant influencing enrollment and graduation outcomes.

The features related to learning ability and initial human capital are also shown in Figures 3.5 and 3.7. Figure 3.5 illustrates the ability distribution for various simulated educational categories. The figure shows that college students, on average, have a higher ability level than no-college students (3.57 vs. 1.18). Also, among college attendants, the average ability of STEM students is higher than that of ARTS (4.06 vs. 2.26), representing a comparative advantages in learning over ARTS and no-college agents. Figure 3.7 shows the initial human capital with minor differences among the three educational categories.

It is worth noting that the concept of "comparative advantage" in my model differs subtly from Roy's self-selection model explained in Chapter 1. The Roy model is a multi-skill or multi-ability model where ability or skill has the same conceptualization and is interchangeably used. In the Roy model, skills represent occupation-specific working abilities, with all agents possessing various levels of all skills. However, some agents have a comparative advantage in a specific occupation-related skill, leading them to choose the occupation associated with that skill. Others may have comparative advantage in different

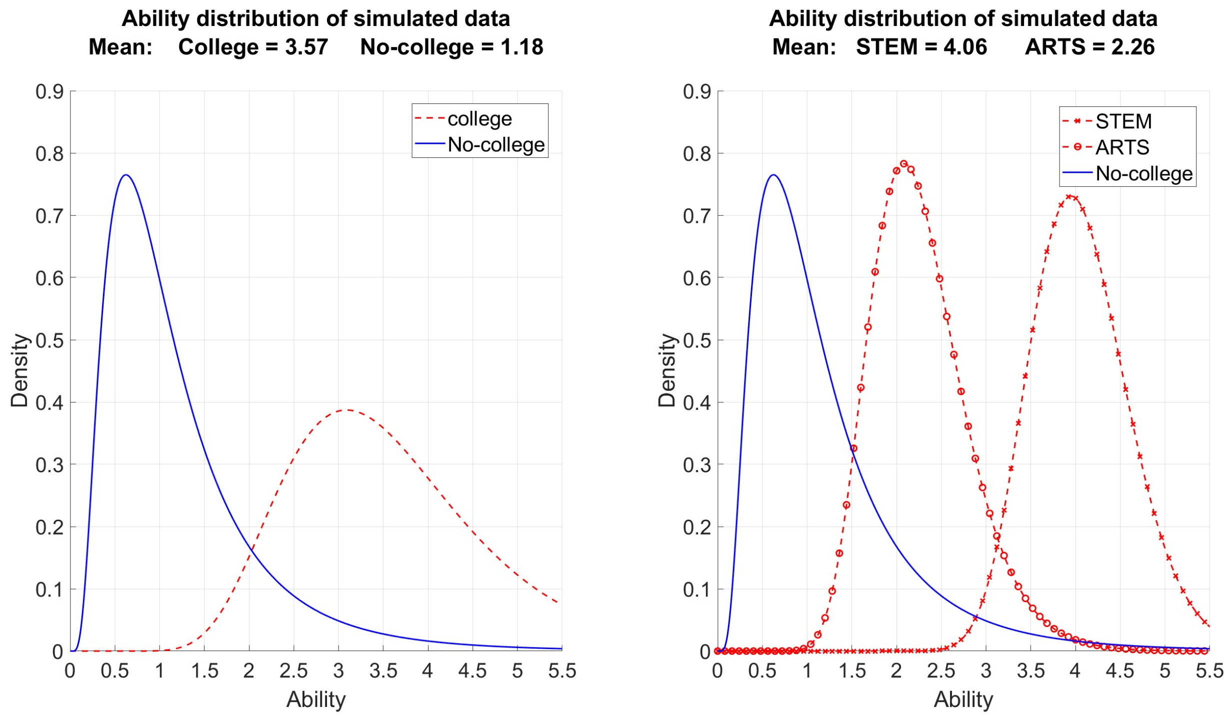

Figure 3.5: Ability distribution of simulated economy[35]

types of abilities and self-select into corresponding occupations. Moreover, individuals may accumulate more occupational-related skills by working in those occupations, a phenomenon known as learning by doing (as in Keane & Wolpin, 1997).

In contrast, my Ben-Porath-type model considers learning ability as a one-dimensional endowment. This learning ability is not tied to STEM-type or ART-type occupations. Individuals share the same learning ability regardless of their career paths (STEM, ARTS, or no college). Differences lie in the ability level, which remains constant over the life cycle. These abilities are employed in human capital production, with different parameters (growth rate of skill price and the depreciation rate of human capital) applied in various occupations. Individuals with higher learning ability are more likely to accumulate college-type human capital, anticipating higher earnings growth. Compared to their lower-ability counterparts, the comparative advantage manifests in higher-ability individuals, giving them more human capital when opting for the college path. In essence, higher-ability individuals exhibit a comparative advantage in learning ability, which guides their self-selection into the college career path.

Figure 3.6 illustrates the decisions of all agents in the model before simulation. These agents are chosen from three points on the initial human capital grid line: low, medium and high This figure provides valuable insights into the decision-making process of mid-ability agents and their educational choices. The results show that mid-ability agents mainly opt for no-college or ARTS paths rather than STEM. This finding can be attributed to their ability level not being sufficient to accumulate the required human capital in STEM fields during their life cycle. Consequently, mid-ability agents may expect lower future earnings and consumption streams, leading to a diminished present utility value when making educational decisions.

These observations are particularly significant as they reveal that all middle-ability ARTS students come from low-initial-asset families. This relationship between initial assets and educational choices has crucial implications for need-based financial aid policies, especially concerning ARTS enrollments. In the "Initial asset" part of this section, further investigation can delve into the role of initial assets in shaping educational choices and the potential implications for need-based financial aid policies. Understanding how initial assets influence mid-ability individuals' decisions to pursue ARTS majors can inform the design of financial aid programs that target and support individuals from low-initial-asset backgrounds.

Figure 3.6 also provides valuable insights into the educational choices of high-ability agents. The results demonstrate that high-ability agents choose STEM paths because their higher ability enables them to accumulate more human capital at a higher skill price. As a result, they can attain higher earnings, consumption levels, and the present value of lifetime utility compared to other career paths. In contrast, if high-ability agents were to select different career paths, they might accumulate more human capital due to lower depreciation rates. However, their accumulated human capital would receive a lower rental rate in the market, resulting in lower income and consumption streams and a diminished present value of their lifetime utility.

[35] To obtain this figure, similar to Ionescu (2009); first, I converted all log-form simulated numbers of ability into positive values using the Natural Exponential Function. Then, I fitted a smooth log-normal distribution to these positive numbers using the *fitdist* command in MATLAB.

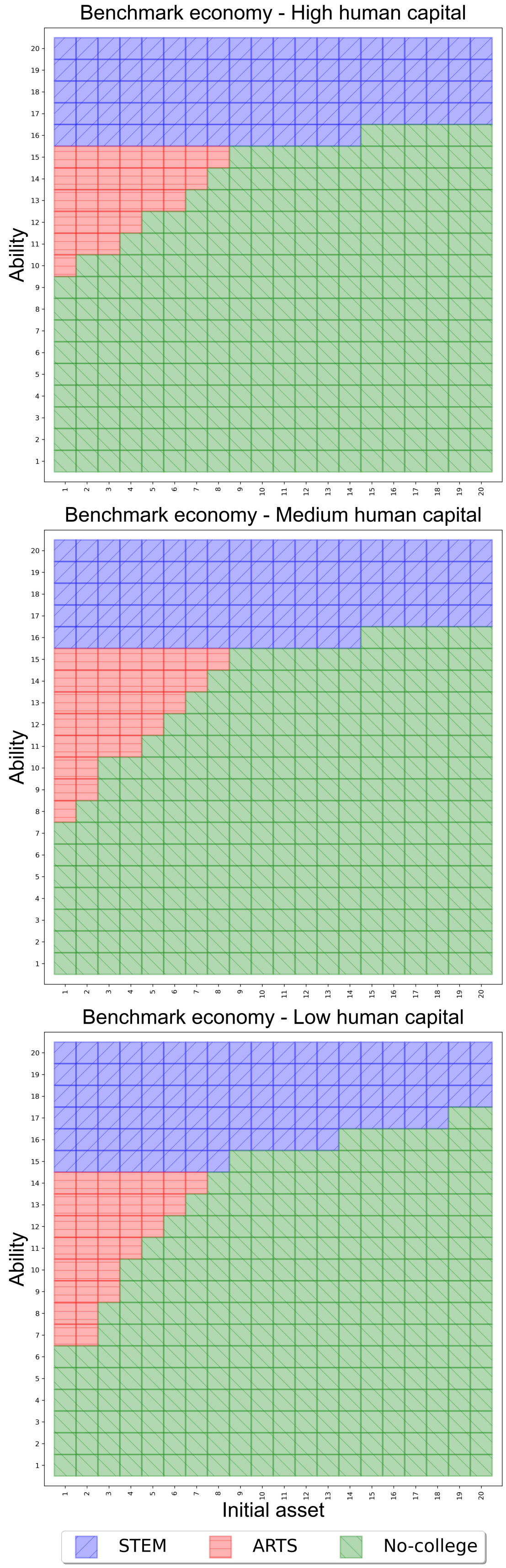

Figure 3.6: Decisions based on initial asset and ability endowments

Initial asset

The results of the model economy, as shown in Figure 3.6, reveal that no ARTS student is from the high-initial asset group. Additionally, Table 3.5 shows that ARTS students' share of the lowest quartile of initial asset is 16.6%, where their share of the economy is only 6.3%. In other words, in the benchmark economy where low-asset agents receive need-based grants to cover their studies, ARTS enrollment is highly observed among the low-asset group. This finding highlights the potential significance of financial aid for low-asset mid-ability individuals pursuing higher education, particularly in ARTS fields. The availability of need-based grants is a crucial mechanism of financial assistance that supports these individuals in overcoming financial barriers and accessing college education.

An experiment is conducted to further investigate the importance of need-based financial assistance for ARTS enrollment by removing this grant type from the benchmark model. The results reveal a dramatic drop in the share of ARTS students when need-based grants are no longer available, almost zero. Moreover, none of the low-asset agents pursue ARTS studies without financial aid. This result underscores the vital role of financial assistance, specifically need-based grants, in supporting low-asset mid-ability individuals. This issue of financial aid accessibility and its impact on college enrollment, especially for ARTS fields, will be further investigated in Section 3.8 (Policy Analysis). By examining the importance of financial aid for low-asset, mid-ability individuals, policymakers can develop targeted interventions to ensure equitable access to higher education opportunities and support individuals from diverse socio-economic backgrounds in achieving their educational and career aspirations.

Initial human capital

Figure 3.6 demonstrates that initial human capital is not a critical endowment in determining individuals' choices regarding college studies. Instead, the main determining factor is the learning ability of the agents. Also, the simulation results of the benchmark economy, depicted in Figure 3.7, confirm this result. This figure illustrates the initial human capital endowment distribution for various educational categories. It shows that college individuals, on average, have a higher level of initial human capital, and STEM has the highest average among the three educational categories. However, the difference between them is not significant. It shows that college individuals, on average, have a higher level of initial human capital, and STEM has the highest average among the three educational categories (211.8, 204.2, 219.9, and 190.2 for college, no-college, STEM, and ARTS, respectively).

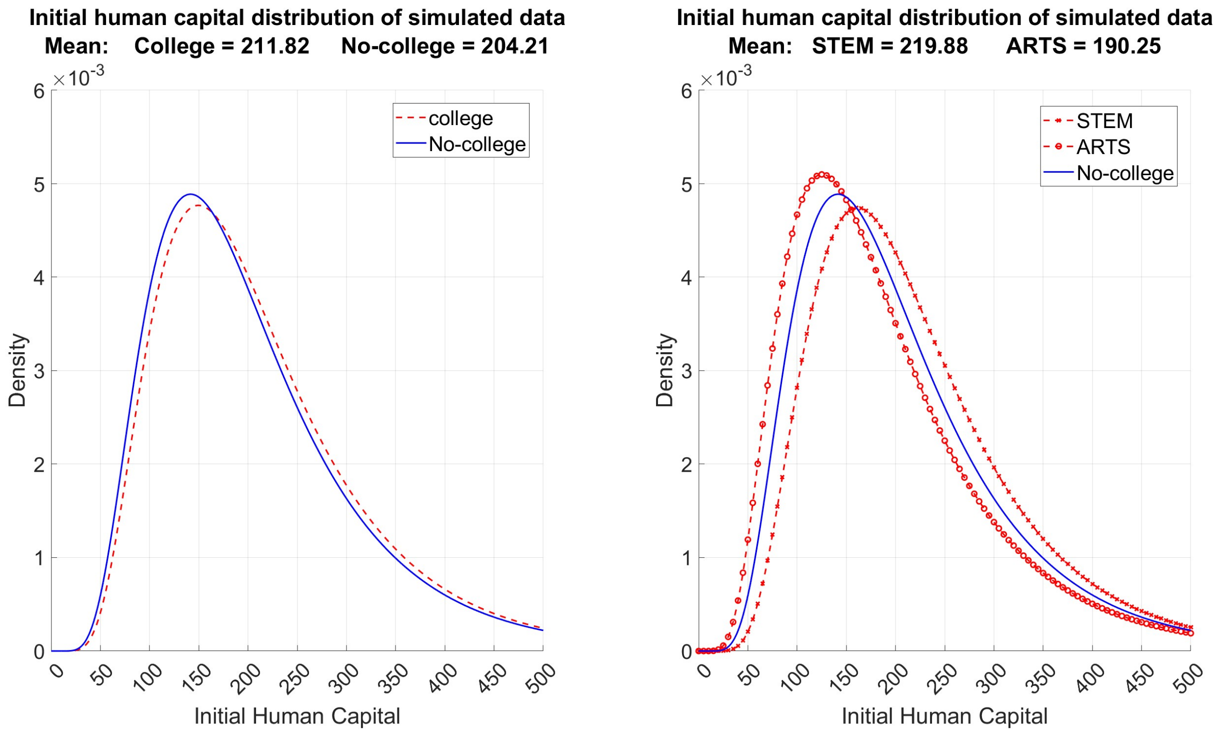

Figure 3.7: Human capital distribution of simulated economy[36]

Furthermore, the life cycle behaviours of agents in the simulated economy, as investigated in the next section, particularly Figure 3.9, further confirm the primary role of learning ability rather than the initial human capital in choosing college studies. The results reveal that an agent with lower initial human capital but higher learning ability (ARTS individuals) can accumulate higher levels during their life cycle than someone with higher initial human capital but lower learning ability (no-college agents). This finding emphasizes the significance of learning ability in influencing an individual's capacity to acquire and develop human capital over time. This feature is related to the more vital role played by the ability in

[36] I obtained this figure by the same approach used to illustrate Figure 3.5.

the human capital accumulation function compared to the role played by the initial human capital, $h_{j+1} = a(h_j s_j)^\alpha + h_j(1-\delta)$.

3.7.2 Life cycle behaviours of agents in simulated economy

This section explores the life cycle behaviours of individuals in different educational categories, focusing on various decisions and outcomes such as accumulated human capital, time invested in human capital, working time, consumption, savings, and earnings.

Figure 3.8 shows that all three educational categories, on average, accumulate more human capital at the beginning of their life cycle. This result is in line with Ben-Porath's finding: individuals optimally invest in human capital production early in life when they have a relatively lower stock of human capital, as explained in Chapter 1. Figure 3.9 illustrates simulated life cycle profiles for human capital. Individuals who choose STEM (ARTS) start with higher (lower) initial human capital levels than those who do not pursue a college education. Both types of college agents leverage their higher-ability comparative advantage to accumulate more human capital over their life cycle. The higher learning ability of college students allows them to get additional human capital more efficiently and effectively. As a result, the gap between college individuals' human capital and that of no-college individuals grows and remains significant over the life cycle, as predicted by Ben-Porath's model: the growth of human capital and wages is higher for higher-ability people.

Figure 3.10 illustrates that during the initial period corresponding to college years, STEM and ARTS students exhibit a relatively lower level of work engagement than their no-college counterparts. Instead, they allocate more time towards accumulating human capital, as evidenced in Figure 3.8. After completing college and throughout the initial half of their life cycle, STEM individuals spend more time in the workforce than ARTS individuals. Elevated skill prices and wages within the STEM field primarily drive this trend. The higher skill prices increase wages for STEM individuals, incentivizing them to participate more actively in the labour market to capitalize on their enhanced earning potential. The

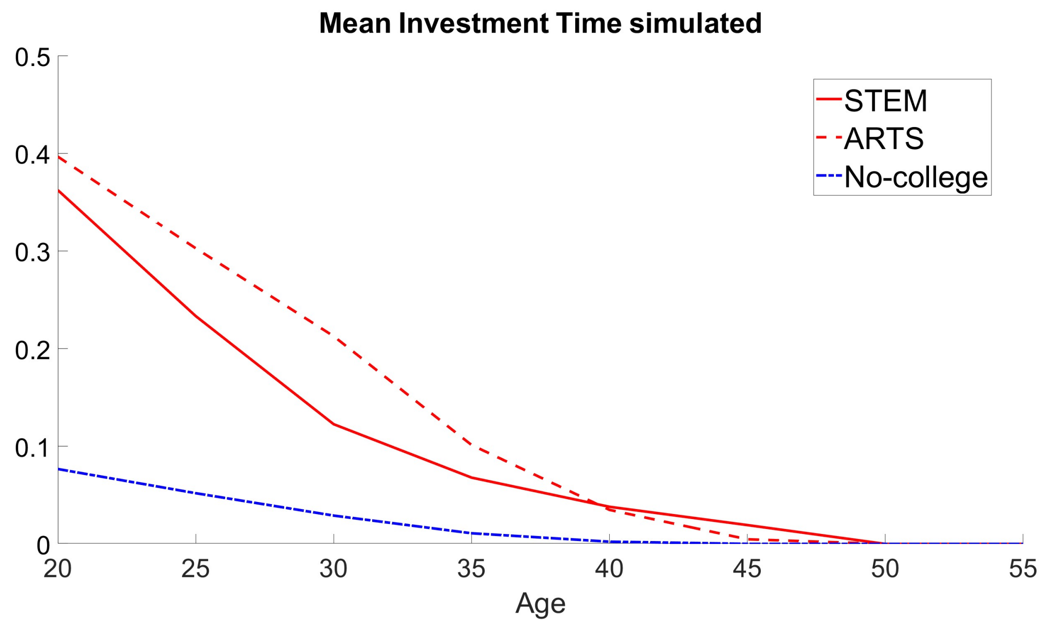

Figure 3.8: Simulated life cycle profiles of average investment time

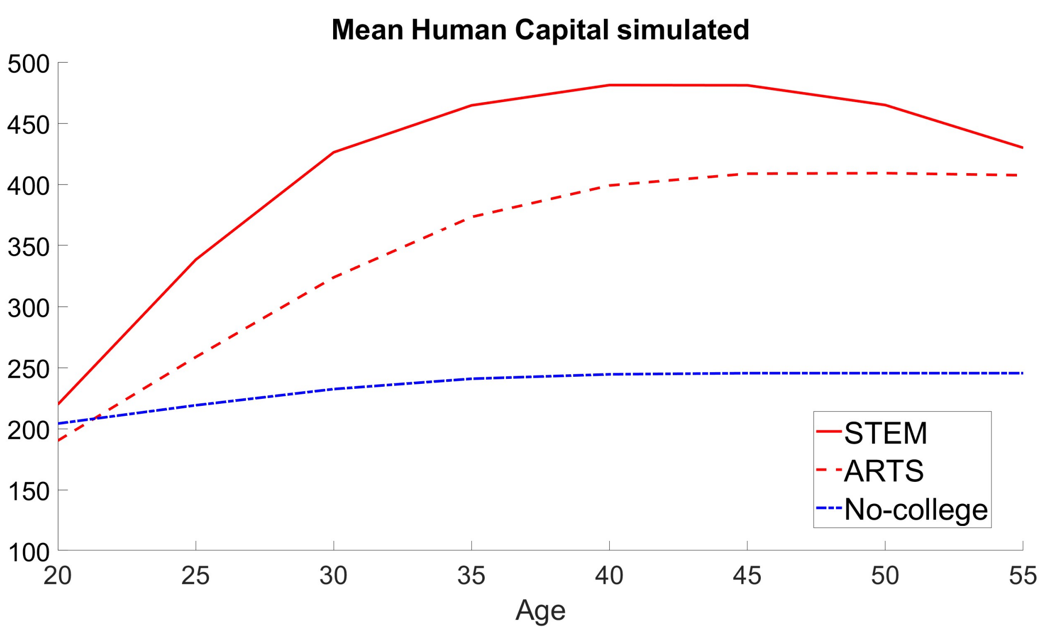

Figure 3.9: Simulated life cycle profiles of average human capitals

amplified wages ($w_j h_j$) translate to augmented consumption levels, valued according to the marginal utility of consumption denoted as $U_1(c_j, s_j, n_j)$. This elevation in consumption leads to heightened marginal benefits, quantified as $U_1(c_j, s_j, n_j)w_j h_j$, as illustrated on the right-hand side of Euler Equation (42). To uphold the equilibrium specified by this Euler equation, the agent reacts by putting higher work effort (n_j), resulting in more negative

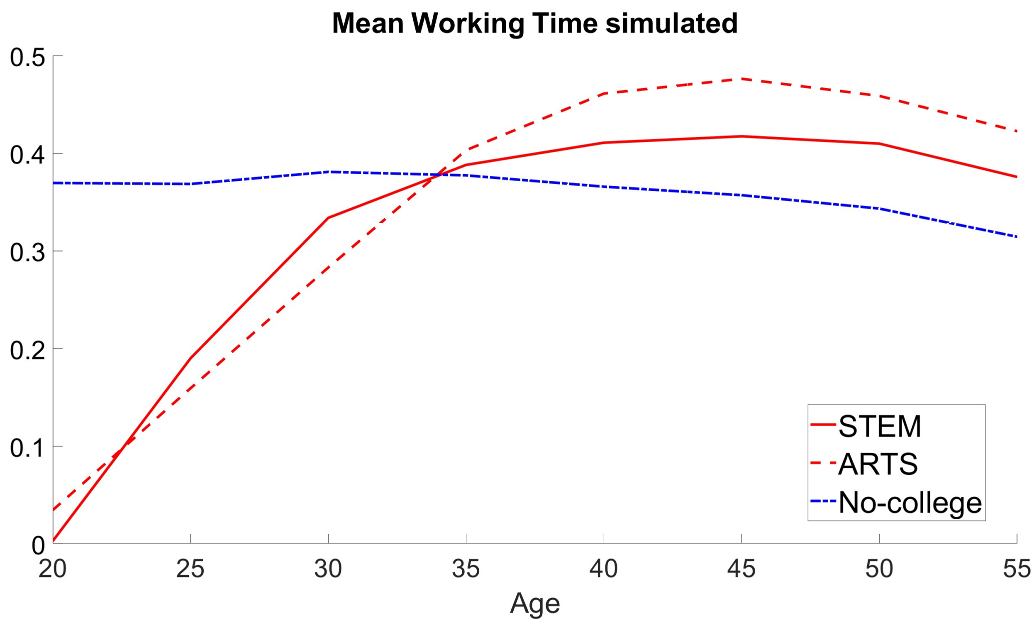

Figure 3.10: Simulated life cycle profiles of average work time

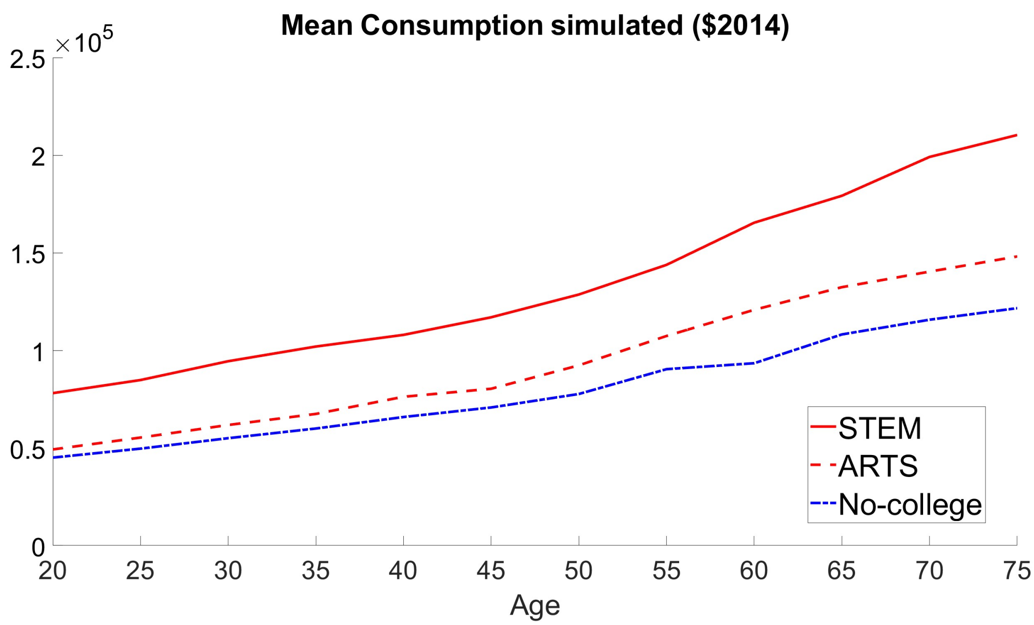

Figure 3.11: Simulated life cycle profiles of average consumption

values for the marginal disutility associated with work time, $U_3(c_j, s_j, n_j)$. Consequently, this yields an elevated positive value for the marginal cost on the left-hand side of the Euler Equation (42), $-U_3(c_j, s_j, n_j)$. In the second half of their life cycle, higher wages and accumulated human capital continue to benefit STEM individuals. These advantages allow them to enjoy higher earnings and consumption levels without working significantly more,

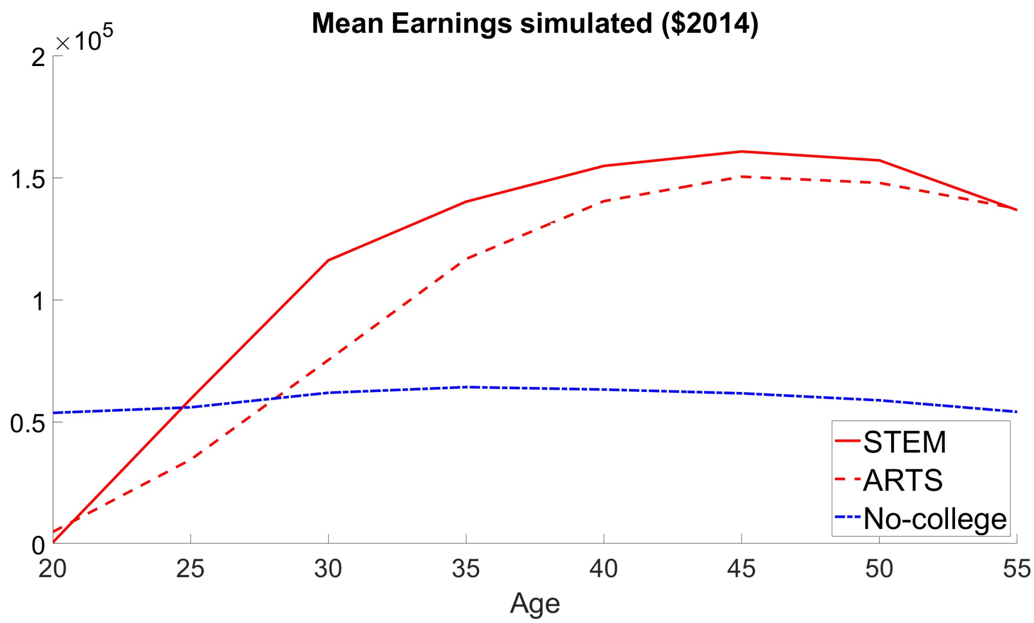

Figure 3.12: Simulated life cycle profiles of average earnings

as depicted in Figures 3.11 and 3.12.

The pattern of the lifetime consumption for all agents is increasing over the life cycle. This result aligns with the Euler Equation (44). This equation shows the relationship between today's and tomorrow's levels of consummation,

$$\frac{U_1(c_j, s_j, n_j)}{U_1(c_{j+1}, s_{j+1}, n_{j+1})} = \beta(1+r) \tag{45}$$

My model is based on logarithmic preferences, as Equation (35) indicates. Also, the model calibration assumptions establish that $\beta(1+r) > 1$. Consequently, the implication of Equation (45) will be that $U_1(c_j, s_j, n_j) > U_1(c_{j+1}, s_{j+1}, n_{j+1})$ and $c_j < c_{j+1}$. In simpler terms, this signifies that consumption tends to rise throughout the life cycle.

Also, the model, endogenously, can generate a hump-shaped life cycle profile for mean earnings, as shown in Figure 3.12. The model I've employed generates a mean earnings profile that takes the shape of a hump, a pattern explained by the conventional human capital mechanism. During the early stages of the life cycle, earnings are modest due to the initial low levels of human capital. At this point, individuals allocate their time toward

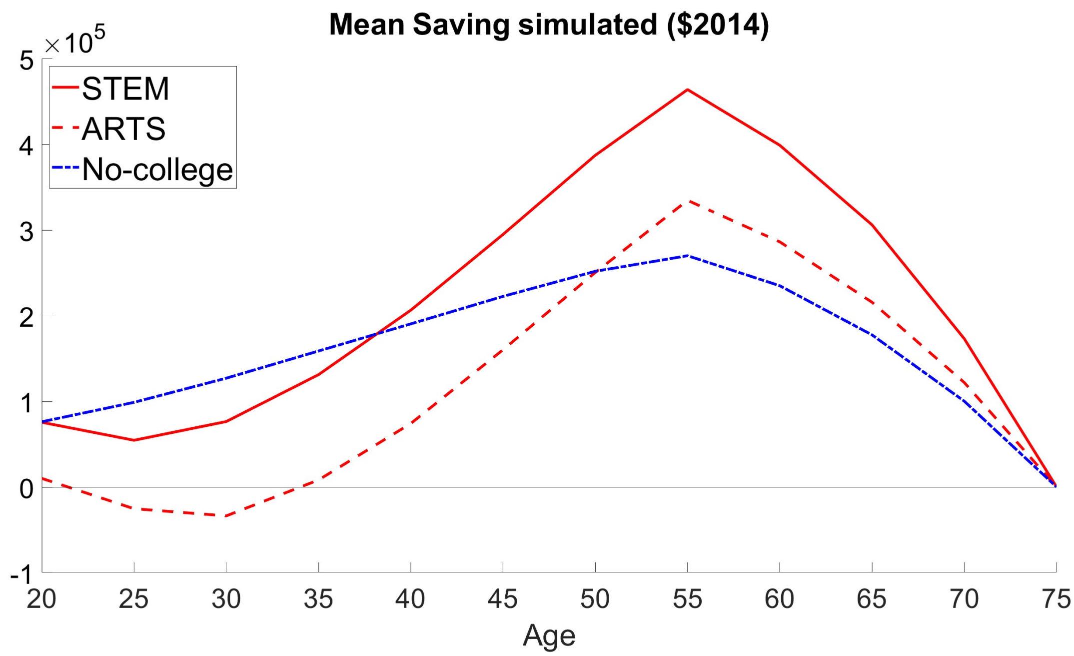

Figure 3.13: Simulated life cycle profiles of average savings

building up their human capital. As human capital increases, earnings experience a rise as more time is dedicated to engaging in market-related work. Subsequently, earnings tend to stabilize and eventually decline later in life. This decline is attributed to the depreciation of human capital over time, coupled with the fact that work effort tends to increase slower than during the early stages of the life cycle. Additionally, as individuals grow older, they may allocate little or no time to producing new human capital, further contributing to the decline in earnings.

Furthermore, Figure 3.13 shows that ARTS individuals, on average, borrow the most among all populations in the early stages of their life cycle. This borrowing behaviour is primarily driven by their lower initial asset levels, as illustrated in Figure 3.6. With more insufficient initial assets, ARTS individuals may face financial constraints during their college years and early working life, prompting them to borrow to meet their educational and living expenses. However, as ARTS individuals progress through their working years, they gradually increase their savings rate and catch up with the savings levels of no-college individuals. This trend reflects the efforts made by ARTS individuals to build up their financial reserves and ensure sufficient resources for retirement and an increasing consumption path. The saving decisions, as depicted in Figure 3.13, are guided by the Euler Equation (44), which captures the trade-offs individuals face between current and future consumption and the value of saving for the future.

The results of the simulated economy presented in the above figures are consistent with the predictions of Ben-Porath's model, as explained in Chapter 1 and well defined by the Euler Equations (42) to (44), described in Section 3.7.1.1 (Euler Equations). The model successfully captures the dynamics of human capital accumulation and its impact on individuals' life cycle outcomes. STEM individuals have higher abilities, and as depicted in the figures, they exhibit higher levels of human capital accumulation compared to ARTS and no-college individuals. Consequently, STEM agents enjoy higher wages, earnings, and consumption. Additionally, Figure 3.13 indicates that, on average, STEM individuals have higher savings over their life cycle. This behaviour reflects their ability to generate higher earnings and their propensity to save and invest for the future.

3.7.3 Counterfactual scenarios

Figure 3.14 presents informative counterfactual scenarios where no-college individuals pursue alternative STEM and ARTS career paths within the benchmark economy. The two graphs at the bottom of this figure demonstrate that if no-college agents had chosen STEM or ARTS paths, their lifetime consumption levels would have been lower, and the total time allocated to work and investment would have been higher than their current choice. These variables directly involve Equation (35), representing the utility function. As a result, the counterfactual decisions of choosing STEM or ARTS paths would have led to lower lifetime utilities compared to their current choice of not pursuing college.

The graph in the upper-left corner of Figure 3.14 illustrates that individuals would have invested more time accumulating human capital if they had chosen the college path. Examining the Euler Equation (43) is valuable in understanding these individuals' decision-making processes. In this hypothetical scenario, these individuals face higher growth

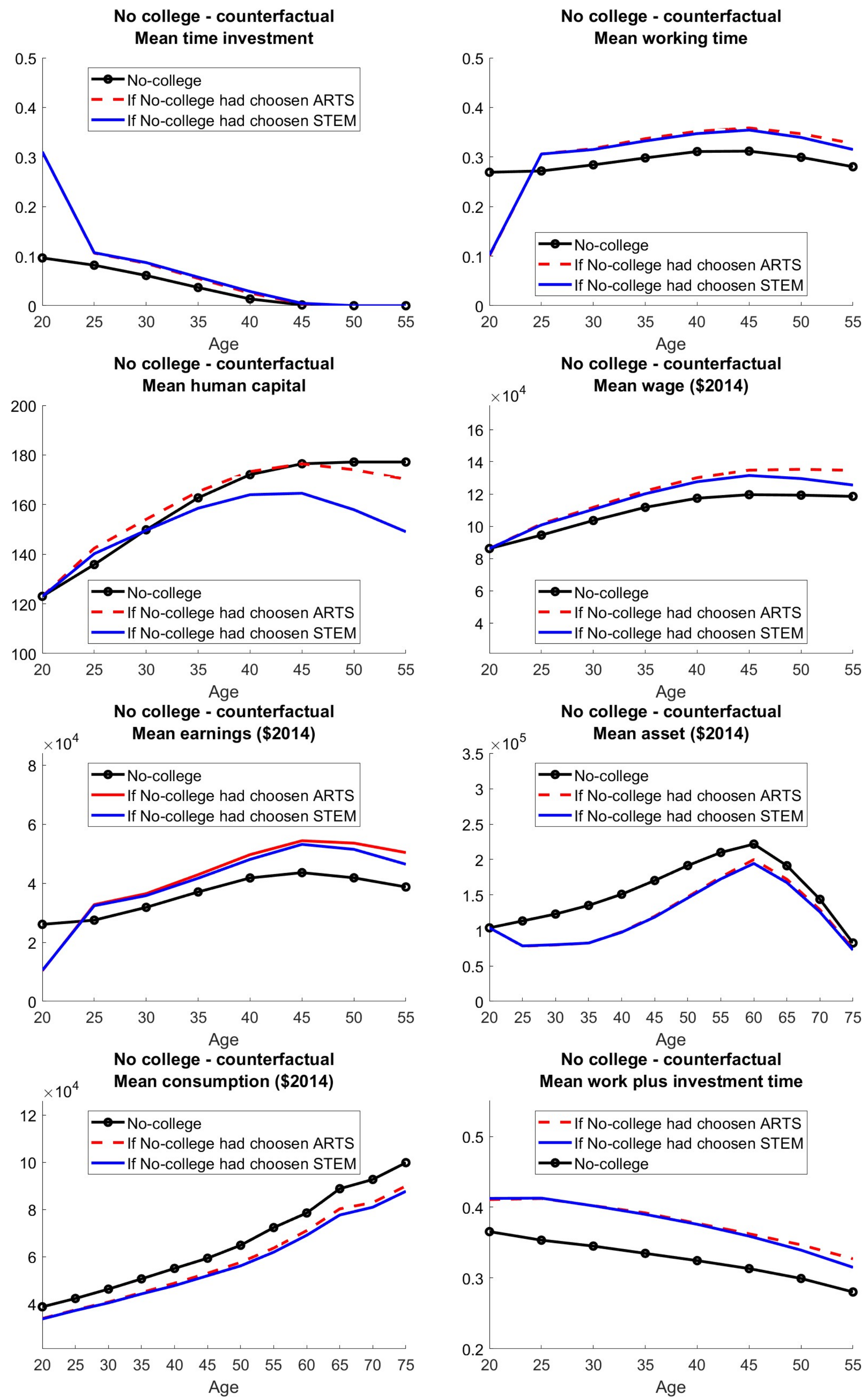

Figure 3.14: Counterfactual for no-college agents had they chosen college paths

rates of skill prices ($g^{college} > g^{no-college}$). These higher growth rates lead to an increase in future skill prices (w_{j+1}), higher earnings per unit of human capital ($w_{j+1}n_{j+1}$), and an enhanced utility of consumption derived from the marginal utility of consumption, $U_1(c_{j+1}, s_{j+1}, n_{j+1})(w_{j+1}n_{j+1})$. Ultimately, these cumulative effects culminate in a higher marginal benefit, depicted on the right-hand side, thereby perturbing the equilibrium of the Euler Equation (43).

Restoring equilibrium involves enhancing the left-hand side of Equation (43), which requires an increase in $-U_2(c_j, s_j, n_j)$ and/or an increase in $1/(\partial h_{j+1}/\partial s_j)$. In this context, allocating more time to invest in human capital (s_j) has the necessary effects. It reduces $U_2(c_j, s_j, n_j)$, resulting in more negative values for the marginal disutility associated with dedicating time to accumulating new human capital, thereby amplifying the positive value of $-U_2(c_j, s_j, n_j)$. Furthermore, as the time allocated to human capital investment (s_j) increases, the marginal product derived from investing time in creating new human capital, $\partial h_{j+1}/\partial s_j$, diminishes, leading to an increase in $1/(\partial h_{j+1}/\partial s_j)$.

As depicted in the graph in the upper-right corner of Figure 3.14, the individuals will notably reduce their investment time in favour of increased work hours, aiming to outpace the earnings associated with the non-college paths post-graduation. This inclination towards higher post-graduation work trajectories among the no-college agents encountering the counterfactual scenarios can be attributed to two factors: greater growth rate of skill prices and more pronounced depreciation rates of college-type human capital ($g^{college} > g^{no-college}$ and $\delta^{college} > \delta^{no-college}$, respectively).

To begin with, the heightened growth rate of skill prices yields augmented post-graduation wages, a trend depicted in the second row of Figure 3.14. The increased wage (w_jh_j) on the right-hand side of the Euler Equation (42) amplifies the utility of consumption derived from the marginal utility of consumption, $U_1(c_j, s_j, n_j)$, translating into a higher marginal benefit of working time, $U_1(c_j, s_j, n_j)w_jh_j$. This elevation in marginal benefit necessitates equilibrium through an increase in the marginal cost, $-U_3(c_j, s_j, n_j)$. This increase in the marginal cost finds its balance in an escalation of working time (n_j), which achieves the desired equilibrium by diminishing $U_3(c_j, s_j, n_j)$ and thereby generating more negative values for the marginal disutility linked to working time, ultimately increasing the positive value of $-U_3(c_j, s_j, n_j)$.

The second rationale pertains to the elevated depreciation rate of college-type human capital under the counterfactual scenario. This heightened depreciation rate leads to a decrease in the return on human capital for the subsequent period, represented by $\partial h_{j+2}/\partial h_{j+1}$. This reduction in the additional h_{j+2} contributes to a decline in the investment time at $j+1$ required to maintain h_{j+2} at a consistent level. Consequently, this results in a diminished fraction of investment time, $[1/(\partial h_{j+2}/\partial s_{j+1})][\partial h_{j+2}/\partial h_{j+1}]$, in comparison to the no-college path. Under the counterfactual scenarios, at time $j+1$, the individual can conserve less investment time than what is observed in the original no-college path. For every unit of saved time, the individual benefits from a reduction in the disutility rate at a magnitude of $U_2(c_{j+1}, s_{j+1}, n_{j+1})$, which denotes the marginal disutility of investing time at the subsequent age.

In the context of the counterfactual scenarios, the advantage gained from reducing investment time at $j+1$ amounts to $-U_2(c_{j+1}, s_{j+1}, n_{j+1})\frac{1}{(\partial h_{j+2}/\partial s_{j+1})}\frac{\partial h_{j+2}}{\partial h_{j+1}}$, as portrayed on the right-hand side of Euler Equation (43). However, this increase in marginal benefit is comparatively lower than the equivalent utility gain in the no-college path due to the individual conserving less investment time to avoid the production of the return to additional human capital, $\partial h_{j+2}/\partial h_{j+1}$. To counteract this decline in marginal benefit and maintain the equilibrium stipulated by Euler Equation (43), the individual will respond in the subsequent period by increasing their work effort (n_{j+1}), raising their earnings per unit human capital ($w_{j+1}n_{j+1}$), and heightening the utility gain stemming from augmented consumption, $U_1(c_{j+1}, s_{j+1}, n_{j+1})(w_{j+1}n_{j+1})$.

As depicted in Figure 3.14, the counterfactual college-type human capital (h_j) experiences slower growth due to elevated depreciation rates. Nevertheless, the post-graduation earnings under counterfactual scenarios surpass the current no-college trajectory due to higher college-type skill prices (w_j) and increased working hours (n_j). These elevated earnings ($w_j h_j n_j$)

resulting from college counterfactual scenarios can increase consumption. However, based on the initially lower consumption level, the counterfactual college consumption trajectory remains lower than the no-college path, commencing at the early life cycle stages. Between ages 25-35, individuals under counterfactual scenarios must allocate resources to repay student loans and interest, which constrains the growth of their savings during this repayment period. Following the repayment phase, individuals can allocate resources to augment their assets following the consumption-saving decision rule outlined in the Euler Equation (44).

To conclude, the counterfactual scenarios wherein no-college individuals in the benchmark economy adopt college paths would result in noteworthy alterations in their life cycle behaviours. Most importantly, these changes include reduced consumption levels and heightened total work and investment time across their life spans, as indicated in the lower portion of Figure 3.14. These variables will factor into the agents' utility function, Equation (35), consequently diminishing the present value of their lifetime utility if the current no-college agents were to opt for college paths.

The insights drawn from Figure 3.15 provide a valuable understanding of how key variables' behaviours would change if STEM and ARTS agents opt for the no-college path. The outcomes suggest that a pivotal factor in swaying high-ability agents towards selecting STEM and ARTS paths over the no-college option is the alteration in their lifetime consumption patterns, emphasizing the significance of this variable in their decision-making process.

3.8 Policy analysis

This section explores the effects of various financial policies on college enrollment for individuals pursuing STEM and ARTS fields. I conducted ten policy experiments, each designed to investigate the impact of specific financial aid policies on individuals' educational choices. For eight experiments, I expanded the coverage of merit-based and need-based grants. By increasing the size of these grants, more financial aid is available to eligible

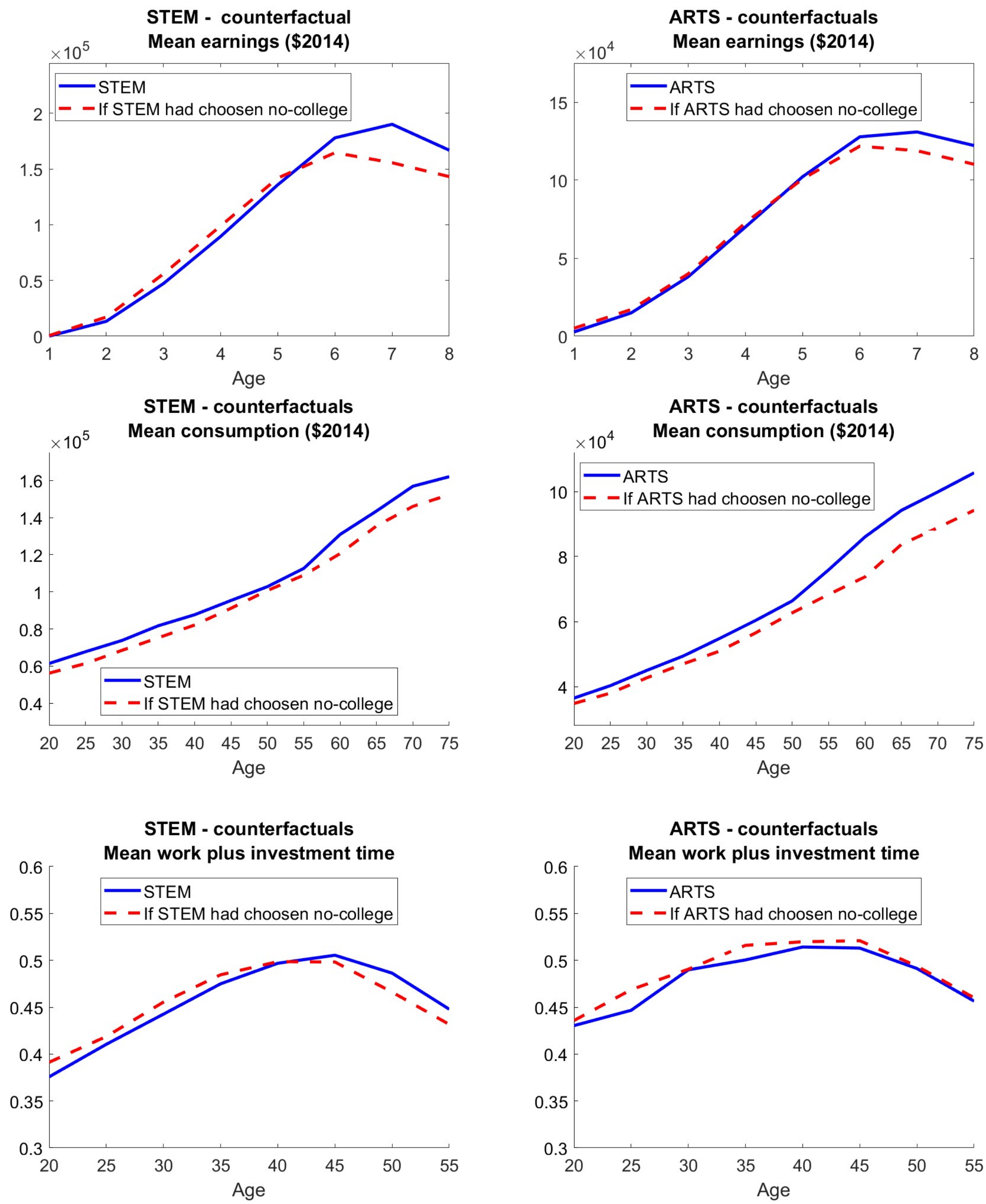

Figure 3.15: Counterfactual for STEM and ARTS agents had they chosen no-college path

individuals, potentially incentivizing more students to enroll in college and pursue STEM or ARTS majors. Similarly, by expanding the coverage of these grants, a broader range of students may qualify for financial assistance, further encouraging college enrollment. Also, I conduct a policy experiment in which I reduce tuition and fees, making college education more affordable for all students. Lowering the financial barrier to college entry could increase college enrollment, particularly among individuals from low-income backgrounds. Additionally, I explore the impact of increasing the student loan limit.

Then, in Section 3.8.6 (Policy comparisons), I explain the results of simulated economies under each financial aid policy and compare the policies' effectiveness and efficiency in increasing individuals' college/STEM/ARTS enrollments. These simulations illustrate how the current sorting into college and college majors in the simulated benchmark economy can be affected by the factors that change in each policy experiment.

3.8.1 Policy 1: Increase in limits of merit-based scholarships

In this part, the policy experiment focuses on a specific group of individuals with relatively higher learning abilities who receive merit-based scholarships in the benchmark economy. I evaluate the impact of an increase in the merit-based financial aid programs in the model economy, simulate the model, and evaluate the results. I increased the limit of merit-based scholarships in the first policy experiment by 30%, as illustrated in Figure 3.16. Increasing merit-based scholarships (Policy 1) increases the new college-enrolled lifetime utility, which depends on three components: consumption, work, and investment times shown in Equation (35).

Figure 3.17 shows that the new college entrants enjoy a higher level of consumption during the life cycle, increasing their lifetime utility. For new students, one notable difference is the faster depreciation of college-type human capital, which requires more time to invest during the life cycle compared to the benchmark economy. Consequently, these new students reduce their working time during specific life cycle periods, focusing more on investing in

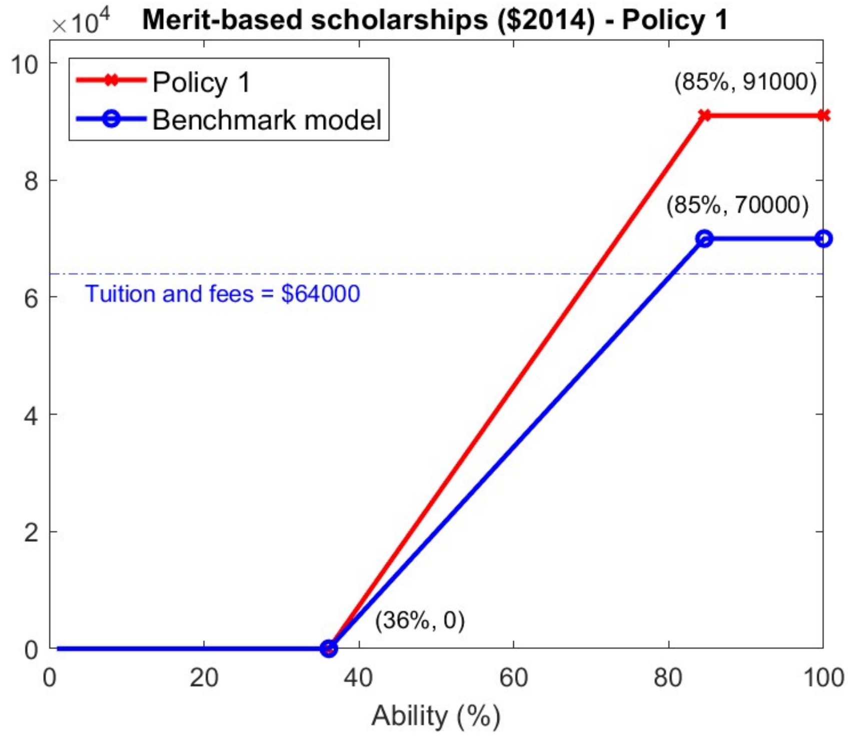

Figure 3.16: Merit-based scholarship distribution - Policy 1 compared to the benchmark economy. Policy 1 = 30% increase in merit-based scholarships

their human capital. Choosing a college path has two financial advantages for new students. First, they receive an elevated merit-based scholarship based on their ability level, providing financial assistance to cover their educational expenses and reduce their financial burden. Second, these new students enjoy a higher skill price and wage stream during their working periods over the life cycle.

The bottom-right graph in Figure 3.17 compares the net effect of changes in work and investment time between the Policy 1 experiment and the benchmark economy. The net result is positive, indicating a negative impact on the present value of lifetime utility as shown in Equation (35). However, the increase in lifetime consumption is higher than the total work and time investment increase. This positive change in lifetime consumption represents an income effect, driving the main factor in increasing the present value of the lifetime gain of choosing a college path for the new students under Policy 1.

Figure 3.16 illustrates that Policy 1, which involves a 30% increase in merit-based

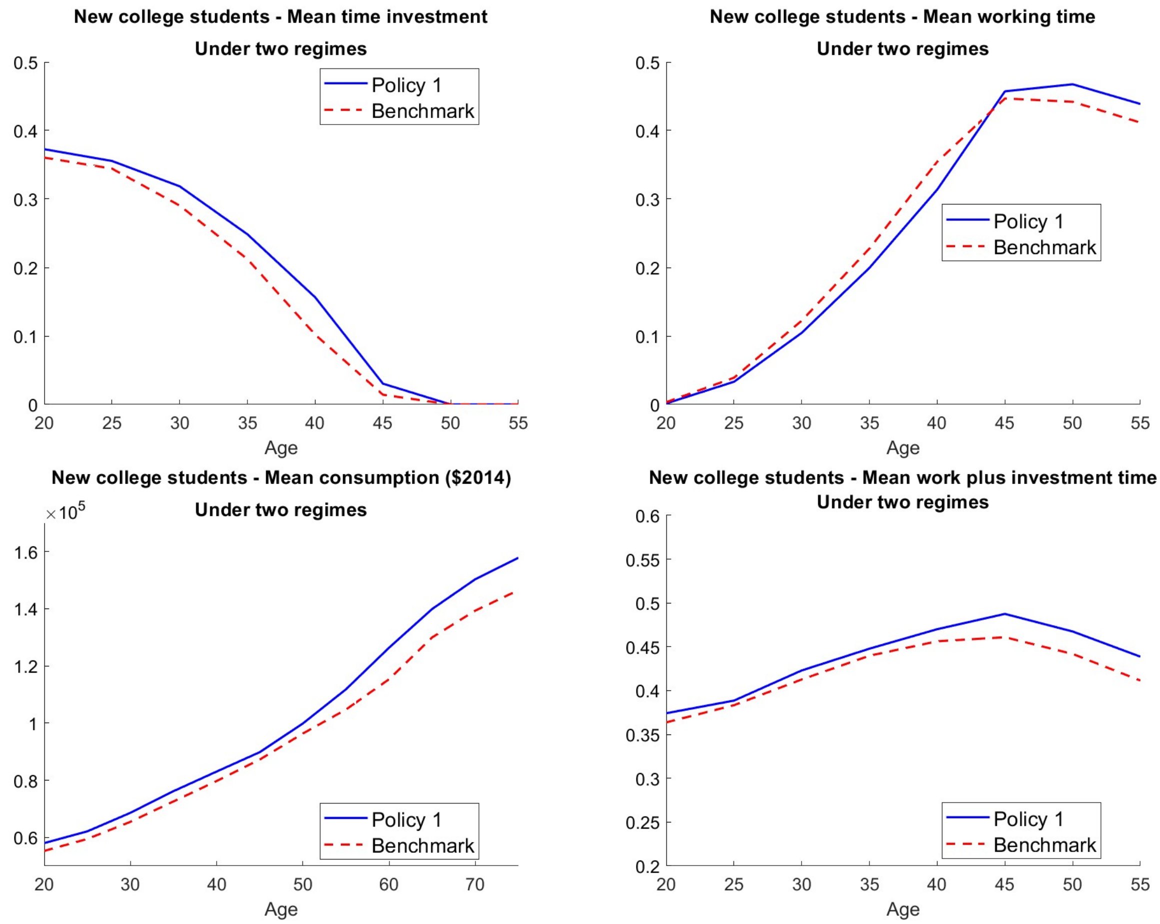

Figure 3.17: Life cycle patterns of mean consumption, work plus investment time for the new entrants under Policy 1 (30% increase in merit-based scholarships) and benchmark economy

scholarships, results in higher financial aid for medium and high-ability agents. However, Figure 3.6 indicates that most high-ability students have already chosen to pursue a college path in the benchmark economy. Consequently, Policy 1 is expected to be more effective for medium-ability individuals who predominantly did not select a college path in the benchmark economy, as shown in Figure 3.6.

To further investigate the effectiveness of the 30% increase in merit-based scholarships for mid-ability agents, let's focus on Figure 3.18. This figure compares the effects of three policies on mid-human-capital agents across various initial assets and ability levels. Figure 3.18 reveals that Policy 1 attracts some high- and mid-ability no-college agents from the benchmark economy to study STEM and ARTS. As expected, individuals from lower ability levels choose ARTS because their ability level is insufficient to compensate for the higher

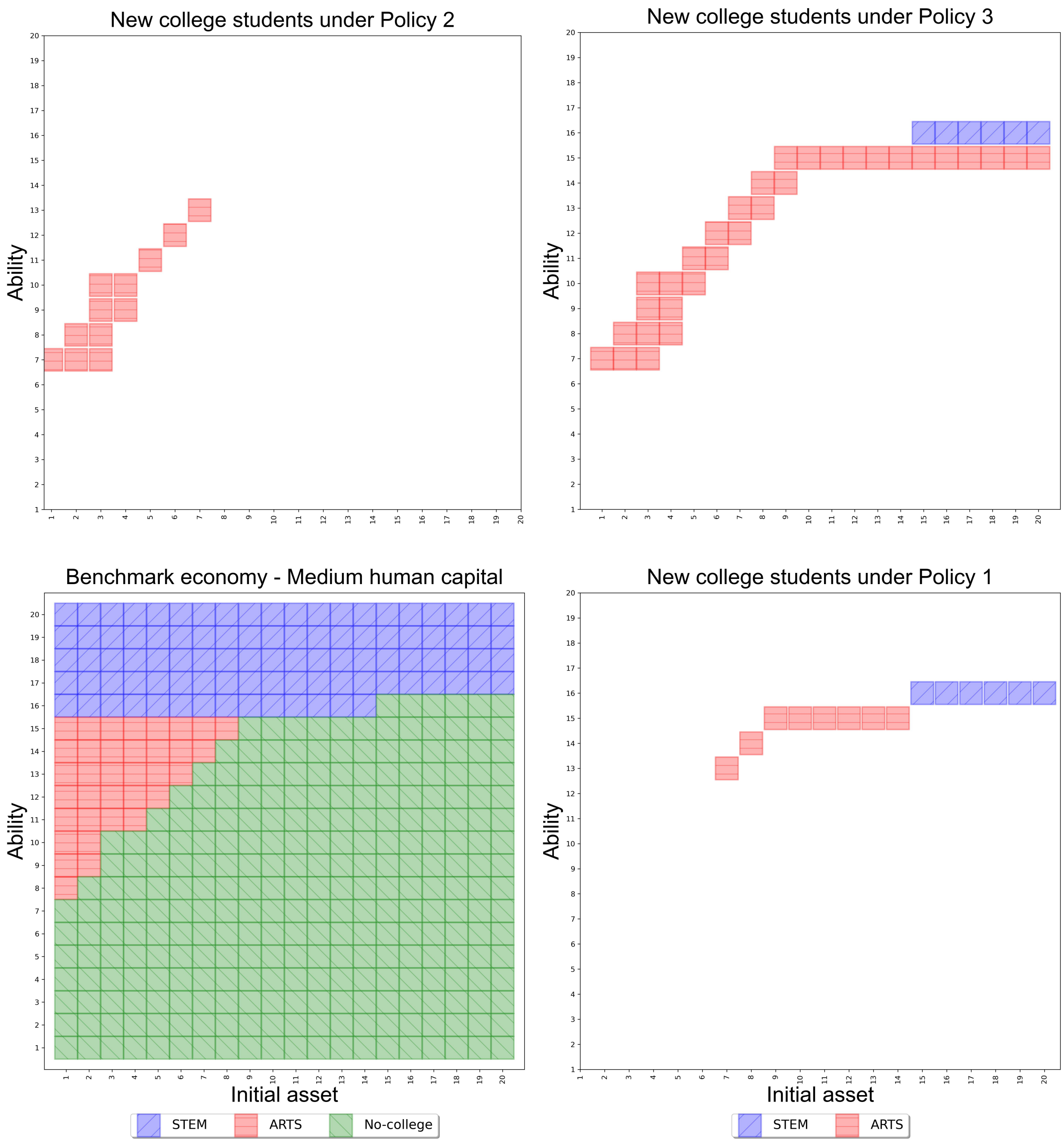

Figure 3.18: Effects of various policies on the decision of medium-human capital agents to switch from no-college career to STEM and ARTS (switchers)
Policy 1 = 30% increase in merit-based scholarships Policy 2 = 30% increase in need-based grants
Policy 3 = 30% decrease in tuition and fees

depreciation rate of STEM-type human capital. Also, Figure 3.18 shows that the effect of Policy 1 is lower than that of the policies that increase the need-based grants (Policy 2) or reduce tuition and fees for all students (Policy 3). This finding suggests that while Policy 1 can still influence some mid-ability individuals to enroll in college and pursue ARTS, it might be less effective than other policies that directly target financial assistance to those with greater financial need or reduce the overall economic burden of a college education.

Furthermore, Figure 3.16 reveals that the 30% increase in scholarships is substantial for top-ability students with an ability level higher than 85%. However, these top-ability students have already chosen to pursue a college path, as shown in Figure 3.6, and benefit from existing financial aid policies. This finding raises a valid concern about the efficiency of spending a significant portion of the scholarship budget on students already committed to college.

One potential approach to enhance scholarship allocation efficiency is effectively targeting scholarship distribution. Instead of uniformly increasing scholarships across all eligible ability levels (between 36% and 100% levels of learning ability), policymakers could consider expanding the coverage of individuals who receive the scholarship or extending the full scholarship to more students. The issue of scholarship allocation efficiency can be further explored in Section 3.8.5 (Extra experiments: expansions of the policy coverage).

3.8.2 Policy 2: Increase in limits of need-based grants

Figure 3.19 demonstrates the impact of the second policy experiment, where the limit of need-based grants distribution is increased by 30%, similar to Policy 1 but primarily targeting low-asset individuals. As shown in Figure 3.18, Policy 2 has a more significant effect on the decision-making of low-asset agents in the mid-ability group compared to the 30% increase in merit-based scholarships (Policy 1). The low-asset agents in the lower tail of the mid-ability group can benefit significantly from this need-based grant, as it helps cover their tuition and fees. It's essential to recognize that the decisions of these low-asset agents are influenced by

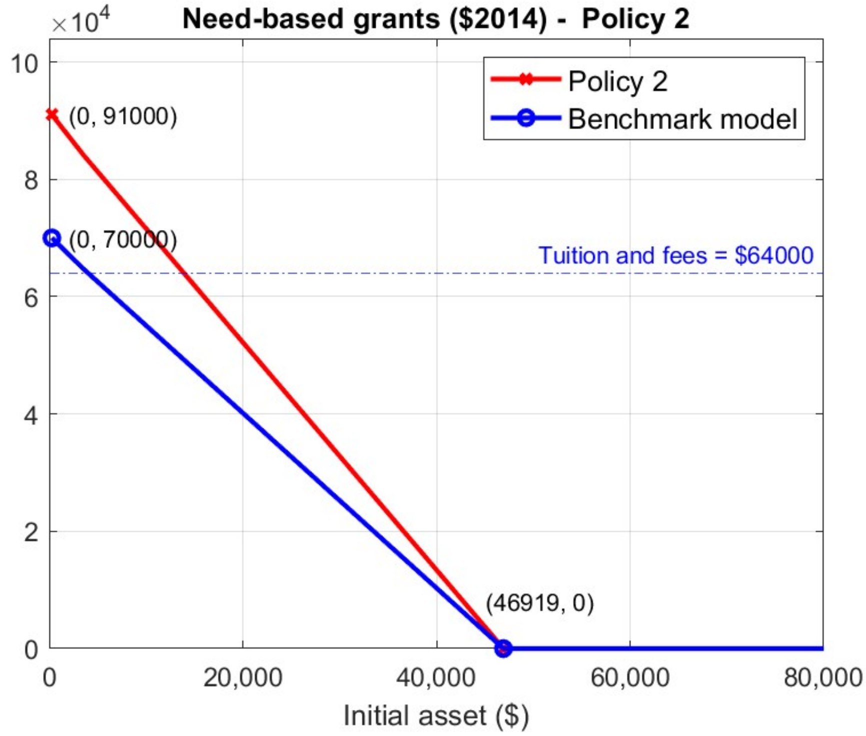

Figure 3.19: Need-based scholarship distribution - Policy two compared to the benchmark economy. Policy 2 = 30% increase in need-based grants

the underlying choices of work and time investment in human capital, which are determined by the marginal costs and benefits explained in the Euler Equation section. The increased need-based grants offer these agents the financial means to invest in their education without experiencing significant financial burdens, leading to a higher likelihood of college enrollment.

As depicted in Figure 3.20, the 30% increase in need-based grants (Policy 2) has a positive impact on the lifetime consumption as the primary utility function component in Equation (35), similar to the effect observed with the 30% increase in merit-based scholarships (Policy 1). Like Policy 1, the significant impact of Policy 2 is that it enables students to reduce their work hours during college and their initial working periods and allocate more time to accumulating and maintaining higher-valued college-type human capital.

Figure 3.20 highlights an interesting phenomenon associated with the 30% increase in need-based grants (Policy 2) compared to the 30% increase in merit-based scholarships (Policy 1). The new students attracted by Policy 2 exhibit a more significant jump in

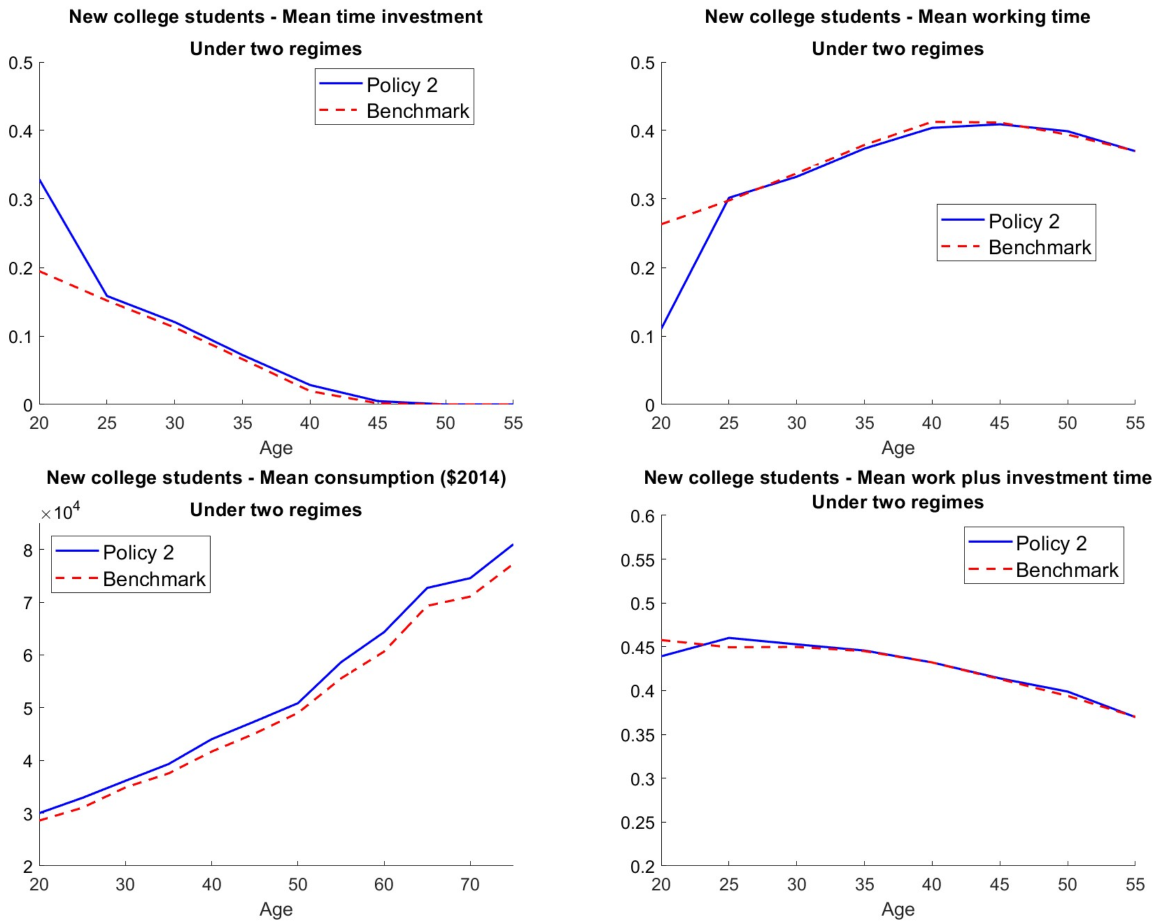

Figure 3.20: Life cycle patterns of mean consumption, work plus investment time for the new entrants under Policy 2 (30% increase in need-based scholarships) and benchmark economy

their time investment to accumulate human capital when they start college studies. In the benchmark economy, as no-college agents, these individuals invested less time getting human capital due to their lower ability levels than those attracted by Policy 1, as shown in Figure 3.18. Also, it is worth mentioning that when they join college under Policy 2, they must allocate at least 25% of their time to accumulate college-type human capital during their college education. This requirement results in a higher percentage change in their time investment in human capital during college.

As shown in Figure 3.20, the net effect of changes in work and investment time is still positive in most periods, indicating a negative impact on the lifetime utility of choosing a college path. However, the negative effect on the present value of lifetime utility associated with increased investment time is much smaller than the positive effects of the increase in lifetime consumption. This observation further emphasizes the income effect associated with the 30% increase in need-based scholarships (Policy 2).

As Figure 3.18 indicates, Policy 2, the 30% increase in need-based grants, attracts some low-asset mid-ability individuals from the benchmark economy to pursue ARTS studies. However, this effect appears to be relatively smaller than the impact of Policy 3, the reduction in tuition and fees for all students. These findings raise the question of whether the 30% increase in need-based grants (Policy 2) could be further modified and improved to enhance its effectiveness and efficiency in encouraging ARTS enrollment among low-asset mid-ability individuals. To address this concern and explore potential modifications to Policy 2, Section 3.8.5 (Extra experiments: expansions of the policy coverage) will delve into additional experiments.

3.8.3 Policy 3: Decrease in tuition and fees

This section investigates the impact of reducing tuition and fees available to a broader spectrum of students rather than a specific group under study. As a broad-based subsidy, a reduction in tuition and fees covers a more comprehensive range of students than those in just merit-based aids or need-based grants, as explained in previous sections.

To define a reduction in tuition and fees for this experiment, I get help from previous studies. Keane and Wolpin (1997) treat the reduction in college tuition as a parameter of the model. This parameter of $2,000 is approximately 50% of the $4,168 (in 1987 dollars), the estimated college tuition. Also, a $1,000 change in tuition and fees in 2000 and 2002 in Abraham and Clark (2006) and Kane (2007) equals 29% and 25% of public four-year colleges and universities.[37] Consistent with the previous experiments, I use the model to simulate an artificial experiment in which the tuition and fees of college students are reduced by 30%.

[37]$1,000 is equal to 29% of $3,501, the current dollars of tuition and required fees of four-year public postsecondary institutions in the year 2000. Similarly, $1,000 is 25% of 4,046 that of 2002. Source: U.S. Department of Education, National Center for Education Statistics (NCES), Digest of Education Studies 2019, Table 330.10 (last accessed December 2023).

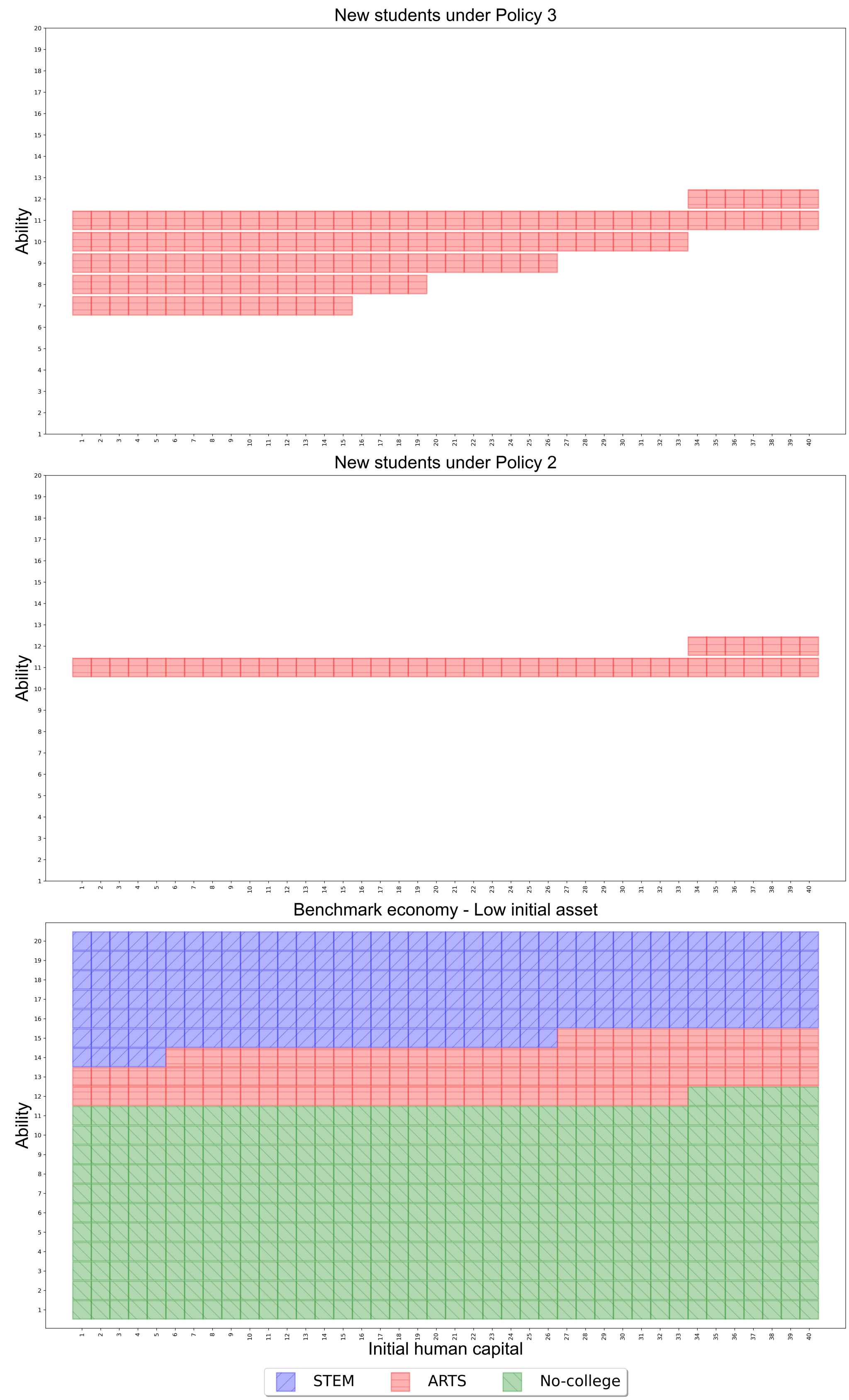

Figure 3.21: Effects of Policy 2 and 3 on career decisions of low-initial-asset agents
Policy 2 = 30% increase in need-based grants. Policy 3 = 30% decrease in tuition and fees

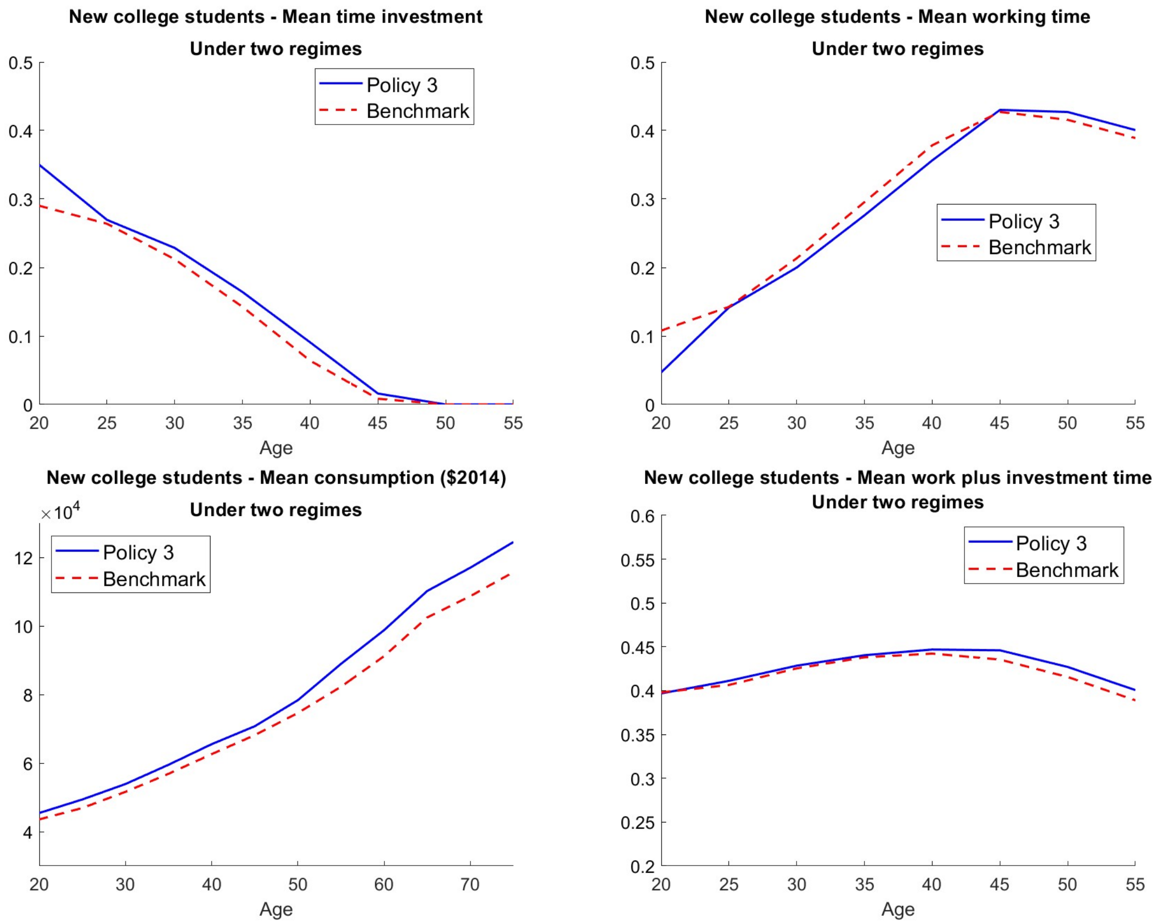

Figure 3.22: Life cycle patterns of mean consumption, work plus investment time for the new entrants under Policy 3 (30% decrease in tuition and fees) and benchmark economy

Policy 3 is a non-targeted financial aid policy. It targets a higher range of abilities than an increase in merit-based scholarship (Policy 1) and a broader spectrum of initial assets compared to financial aid targeting only low-asset individuals (Policy 2.) As a result, as shown in Figure 3.18, a reduction in tuition and fees (Policy 3) is more successful than the other two policies in attracting individuals to college.

Figure 3.21 also compares the effect of Policy 3 with that of Policy 2 on the low-asset agents' educational choices. This figure shows the impact of reducing tuition and fees (Policy 3) is more than giving need-based grants to low-asset individuals (Policy 2) because a reduction in tuition and fees covers more individuals than distributing need-based grants.

Like an increase in merit-based scholarships (Policy 1) and the increase in need-based grants (Policy 2), the 30% decrease in tuition and fees (Policy 3) increases the new college entrants' lifetime utility. Figure 3.22 shows that under Policy 3, the new students allocate more time to invest in human capital accumulation. This extra time to invest is associated with a decrease in working time up to some working periods. The new students invest more in higher-paid college-type human capital because it has a higher depreciation rate. The college-type human capital requires more investment time to maintain or grow.

3.8.4 Policy 4: Increase in student loan limit

In this experiment, I increase the student loan limit by 35%, from $31,000 to $41,850. It is similar to the actual policy done in 2008, from 23,000 to 31,000 dollars. As evident in Table 3.6, this policy experiment leads to a 0.7 percentage point rise in college enrollment, the lowest increase among all policy experiments. This policy increases college enrollments only in ARTS. In this regard, the effect of this policy is similar to that of Policy 2, a 35% increase in need-based grants (2 percentage points, all in ARTS). Both target low-asset individuals.

However, Policy 4 has a lower positive effect on college enrollment than Policy 2 because the student loan is contingent on being repaid with interest within two model periods by the model setup. However, a need-based grant is free money. In other words, the previous three policies (free merit- and need-based grants and a reduction in tuition and fees) enter free money into the agent's budget constraints and increase the net present value of attending college. Still, Policy 4 does not have this feature. Therefore, compared to other policy experiments, a more generous government student loan program in increasing the loan limit leads to a minor increase in college participation rates.

Figure 3.23 demonstrates that Policy 4, the 35% increase in federal loan limits, also operates through a mechanism similar to previous policies. It leads to an income effect by increasing the lifetime consumption of new college entrants, who now invest more in college-type human capital than they did in the benchmark economy when they were out of college. Moreover, they benefit from the higher skill price when they work during the life cycle.

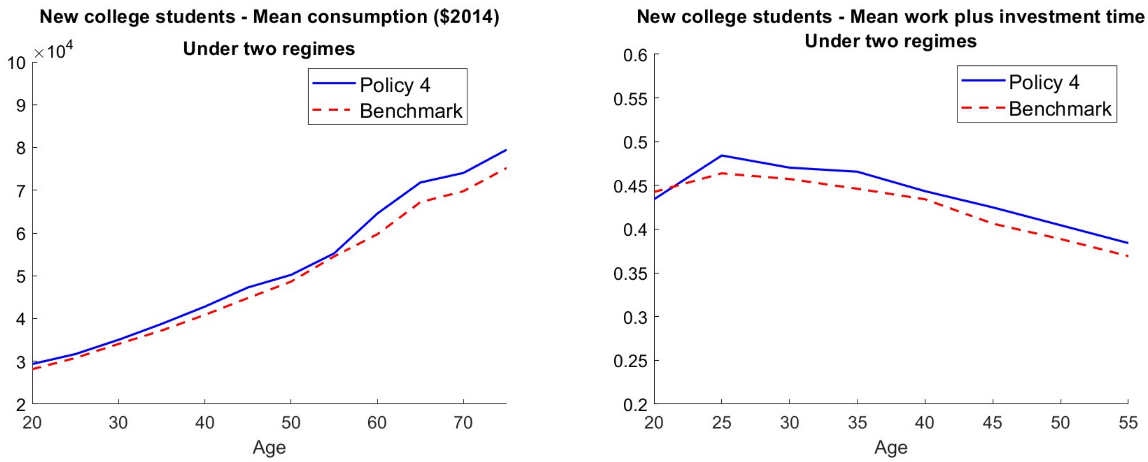

Figure 3.23: Percentage change in mean consumption, work, and investment time patterns for the new entrants under Policy 4 (35% increase in student loan limit)

3.8.5 Extra experiments: expansions of the policy coverage

This section introduces extensions to Policy 1 (a 35% increase in merit-based scholarships) and Policy 2 (a 35% increase in need-based grants). The goal is to explore the potential effects of expanding these financial aid policies. As previously mentioned in sections Policy 1 and Policy 2, there is a need for some modification and improvement in the effectiveness and efficiency of these policies. I will introduce six extra policies in this part to address this issue. Three of these policies will serve as extensions of Policy 1, while the remaining three will be expansions of Policy 2.

Expanding the coverage for Policy 1

Figure 3.24 illustrates the ability distributions of college students in two simulated economies: one under Policy 1 and the other under the benchmark economy. The ability distribution for Policy 1 indicates that providing more financial aid to individuals with abilities higher than 85% did not significantly alter their career choices. Instead, the prominent increase in college enrollment occurred within the ability range of 70% to 85% for STEM and between 36% and 70% for ARTS.

Figure 3.25 presents three expansions for the coverage distribution in merit-based

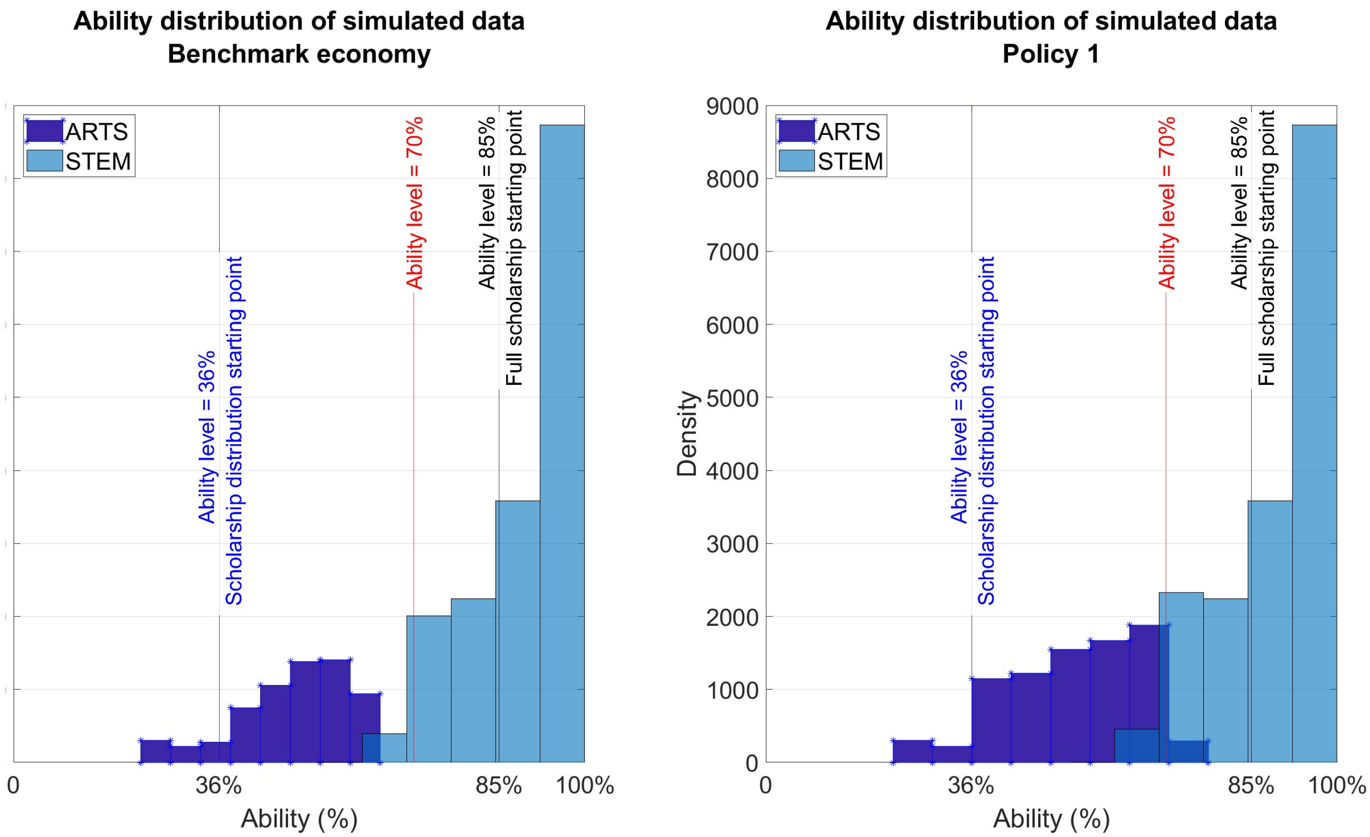

Figure 3.24: Ability distributions of college students in simulated economies - Policy 1 compared to the benchmark economy. Policy 1 = 30% increase in merit-based scholarships

scholarship distribution. Policy 1_maxAid_expansion maintains the initial ability threshold for receiving financial aid at 36%. However, it eliminates the extra funding provided to high-ability agents. Instead, it expands the coverage of the full scholarship ($70,000) to include individuals with a minimum of 71% ability level, widening the range of students eligible for the scholarship. This modification aligns the slope of the line connecting this threshold to the maximum scholarship with that of Policy 1. Policy 1_maxAid_expansion investigates the impact of providing full merit-based scholarships to a broader range of students with moderately high abilities.

Indeed, as shown in the middle graph of Figure 3.25, the setup for Policy 1_eligibility_maxAid_expansion involves two coverage expansions. The first expansion increases the maximum amount of scholarship ($70,000) to the left, extending it from 85% to 71% of the ability range, similar to the previous expansion. The second extension is for the

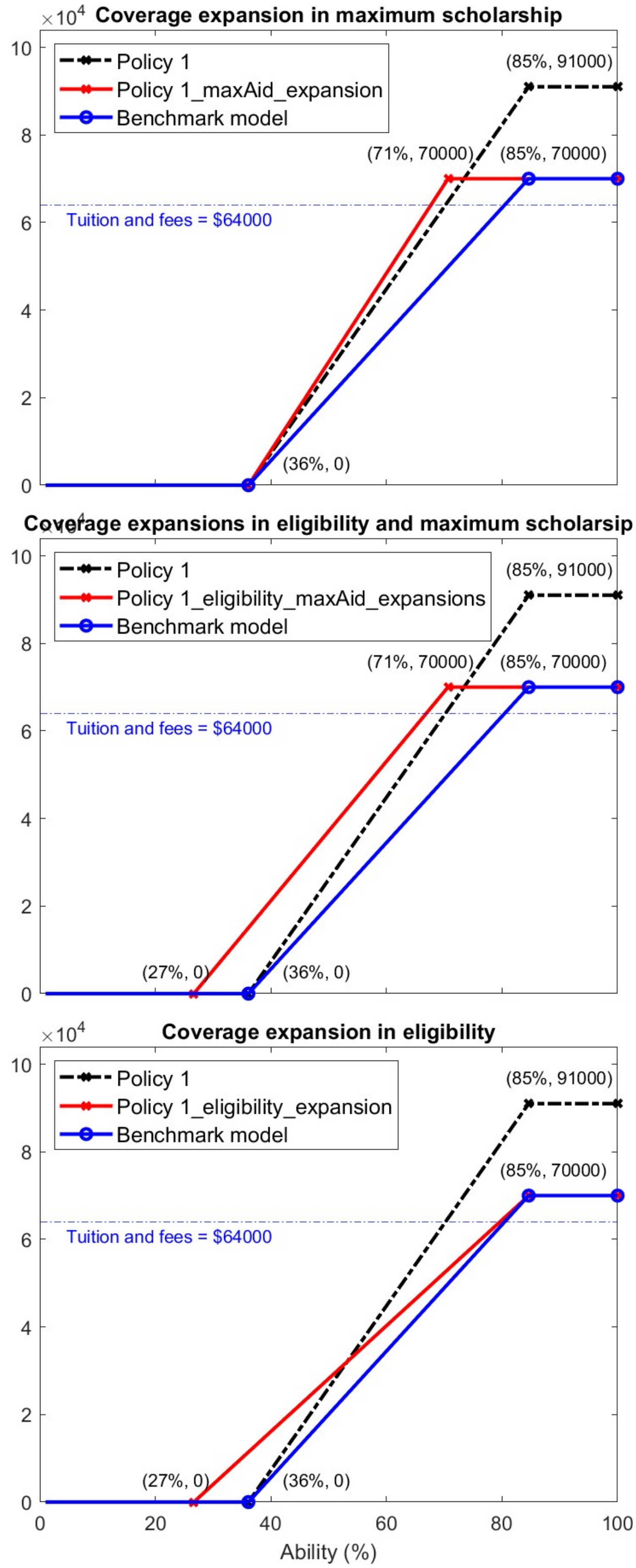

Figure 3.25: Three extensions to the merit-based scholarship policy (P1)

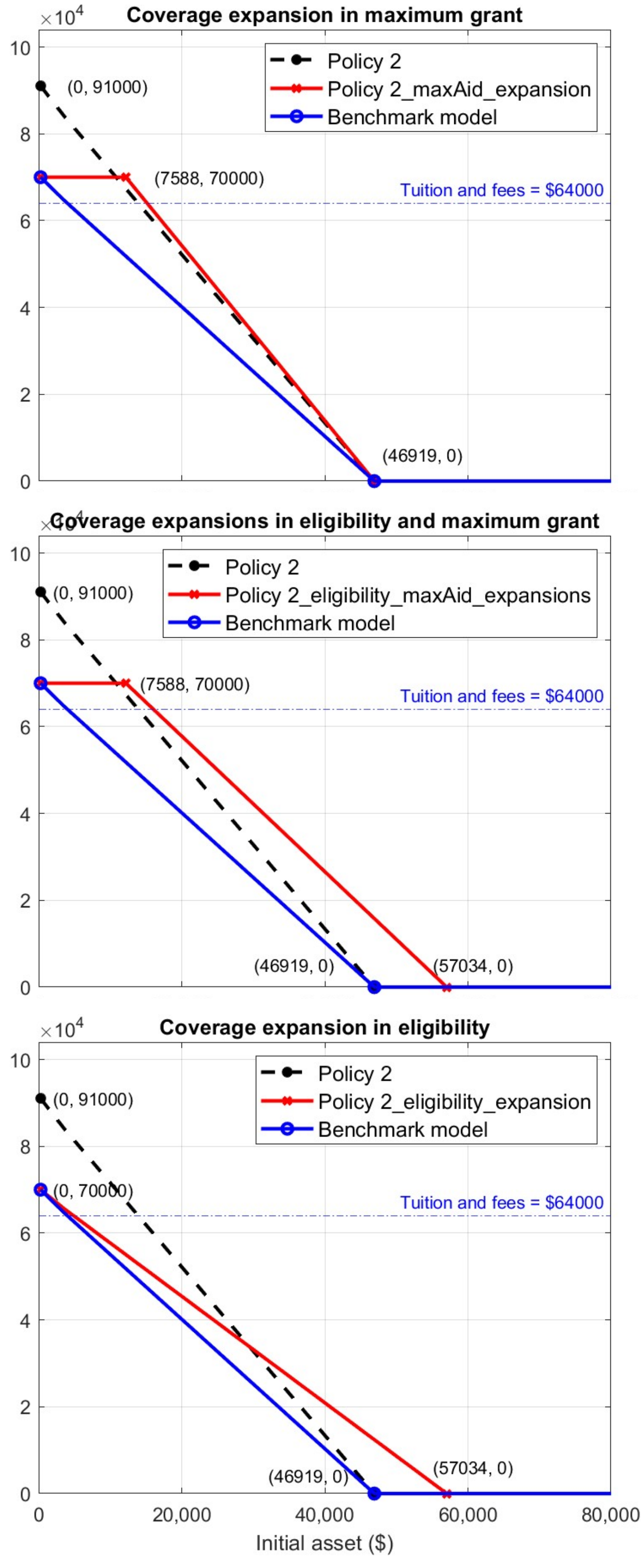

Figure 3.26: Three extensions to the need-based grant policy (P2)

minimum ability threshold, moving it from 36% to 27%. This modification aligns the slope of the line connecting this threshold to the maximum scholarship with that of the benchmark economy. Thus, this policy is named Policy 1_eligibility_maxAid_expansion. Similarly, the last graph in Figure 3.25 depicts the third policy, Policy 1_eligibility_expansion, where only the minimum ability threshold is shifted to the left at 27%. This policy maintains maximum scholarship coverage at the same level as the benchmark economy (85% of ability).

Expanding the coverage for Policy 2

Figure 3.26 indeed demonstrates the need-based grant financial aid policy extensions, and the first graph on the top depicts the policy labelled as P2_maxAid_expansion. This extension expands the maximum grant of $70,000 to all students whose initial assets are approximately $7,000 or less. However, the initial-asset threshold for receiving the funding remains unchanged at around $47,000, similar to the benchmark economy. By implementing this extension, policymakers can target financial aid more effectively to students with lower initial assets, making college more affordable and accessible for economically disadvantaged individuals.

In Figure 3.26, the second graph in the middle, labelled P2_maxAid_expansion, simultaneously depicts two need-based grant financial aid policy expansions. The first expansion involves extending the coverage of the maximum grant ($70,000) to all students whose initial assets are approximately $7,000 or less. Additionally, the eligibility threshold for receiving the full funding is expanded from around $47,000 to $57,000. This policy aims to provide more financial assistance to students from low-income backgrounds (with initial assets up to $7,000) while accommodating students with slightly higher initial assets (up to $57,000). The last policy in the third graph is referred to as P2_eligibility_expansion. This policy only expands the eligibility threshold, moving from around $47,000 to $57,000. By increasing this threshold, more students with initial assets below $57,000 become eligible for the need-based grant, making it more accessible to a broader range of students.

3.8.6 Policy comparisons based on effectiveness and efficiency measures

It's important to note that all simulations conducted in this thesis, both for the benchmark economy and various policy experiments, are undertaken in the context of a partial equilibrium model. This modelling approach assumes that changes in policy within the model do not impact the skill prices. Heckman, Lochner, and Taber (1999) estimate an open-economy overlapping generation general equilibrium model of endogenous human capital in the form of schooling and on-the-job training. They use the model to explain rising wage inequality due to skill-biased technical change. The authors evaluate two policies: (a) tuition subsidies to promote skill formation and (b) tax policies.

Heckman et al. (1999) find that the partial equilibrium effect of a change in college tuition overstates general equilibrium effects on college attendance by about a factor of ten. Whereas, Lee (2005) develops and estimates a dynamic general equilibrium overlapping-generations model of career decisions and finds that the partial equilibrium effect of a tuition subsidy on college enrollment will exceed the general equilibrium effect of only about 10%. He concludes that the partial equilibrium analysis of schooling choice is similar to the general equilibrium analysis for the tuition policy experiment. Increasing college enrollment may decrease (increase) the college (no-college) skill prices in a general equilibrium setup. These changes in the equilibrium college skill prices mitigate the incentive to attend college.

Policy comparisons based on Effectiveness measures

Table 3.6 presents the distribution of educational categories within the simulated economy across various policy experiments. The ranking of these experiments is based on their effectiveness in augmenting overall college enrollment. Notably, the results demonstrate that a 30% reduction in tuition and fees (Policy 3) generates substantial gains of 9.9, 0.3, and 9.6 percentage points in college, STEM, and ARTS enrollments, respectively. This result underscores Policy 3's exceptional efficacy in incentivizing high school graduates, especially in the ARTS domain, to pursue higher education. In contrast, Policy 4, which involves

Table 3.6: Effects of various policy experiments on enrollment rates

Benchmark economy and policy experiments	College (STEM+ARTS) (%)	STEM (%)	ARTS (%)	No-college (%)
Baseline economy	23.3	17.0	6.3	76.7
Policy 3	33.2	17.3	15.9	66.8
Policy 2_eligibility_maxAid_expansions	29.7	17.0	12.7	70.3
Policy 1_eligibility_maxAid_expansions	28.7	17.3	11.4	71.3
Policy 2_maxAid_expansion	28.6	17.0	11.6	71.4
Policy 2	28.6	17.0	11.6	71.4
Policy 1_maxAid_expansion	26.0	17.3	8.7	74.0
Policy 1_eligibility_expansion	25.7	17.0	8.7	74.3
Policy 1	25.7	17.4	8.3	74.3
Policy 2_eligibility_expansion	24.8	17.0	7.8	75.2
Policy 4	24.0	17.0	7.0	76.0

Policy 1 = 30% increase in merit-based scholarships,
Policy 1_maxAid_expansion = Coverage expansion in the merit-based scholarship maximum amount,
Policy 1_eligibility_maxAid_expansions = Coverage expansion in the merit-based scholarship maximum amount and the lowest ability threshold,
Policy 1_eligibility_expansion = Coverage expansion in the merit-based scholarship lowest ability threshold,
Policy 2 = 30% increase in need-based grants,
Policy 2_maxAid_expansion = Coverage expansion in the need-based grant maximum amount,
Policy 2_eligibility_maxAid_expansions = Coverage expansion in the need-based grant maximum amount and the highest initial-asset threshold,
Policy 2_eligibility_expansion = Coverage expansion in the need-based grant highest initial-asset threshold,
Policy 3 = 30% decrease in tuition and fees,
Policy 4 = 35% increase in student loan limit.

elevating federal loan limits, yields a comparably marginal impact on college enrollments (0.7%), with all the increase occurring in ARTS fields. This limited effect can be attributed to individuals being obliged to repay loans post-graduation. From a student perspective, the appeal of receiving more student loans is diminished compared to policies that distribute non-repayable funds to students.

Policy comparisons based on the total policy costs

While Table 3.6 shows the positive impact of some policy experiments on college, STEM,

Table 3.7: Total cost of financial policies (scholarships, grants, and reduction in tuition and fees)

Policy experiments	Policy cost (Billion dollars)
Policy 3	2.920
Policy 2_eligibility_maxAid_expansions	2.418
Policy 2	2.317
Policy 1_eligibility_maxAid_expansions	2.315
Policy 1	2.291
Policy 2_maxAid_expansion	2.285
Policy 1_maxAid_expansion	2.073
Policy 1_eligibility_expansion	1.996
Policy 2_eligibility_expansion	1.941

Policy 1 = 30% increase in merit-based scholarships,
Policy 1_maxAid_expansion = Coverage expansion in the merit-based scholarship maximum amount,
Policy 1_eligibility_maxAid_expansions = Coverage expansion in the merit-based scholarship maximum amount and the lowest ability threshold,
Policy 1_eligibility_expansion = Coverage expansion in the merit-based scholarship lowest ability threshold,
Policy 2 = 30% increase in need-based grants,
Policy 2_maxAid_expansion = Coverage expansion in the need-based grant maximum amount,
Policy 2_eligibility_maxAid_expansions = Coverage expansion in the need-based grant maximum amount and the highest initial-asset threshold,
Policy 2_eligibility_expansion = Coverage expansion in the need-based grant highest initial-asset threshold,
Policy 3 = 30% decrease in tuition and fees,
Policy 4 (35% increase in student loan limit) is not in the table because the cost calculation of the financial aid policies is based on merit-based scholarships and need-based grants.

and ARTS enrollments, it is equally important to assess the cost and benefit associated with implementing these policies. As policymakers evaluate the effectiveness of these financial aid policies, they must also carefully consider the cost/benefit analysis of their decisions based on their budgetary implications. In other words, the results will be more consistent if one compares the policies based on their efficiency and effectiveness.

Table 3.7 shows the total cost of implementing different policies. It shows that non-targeted reduction in tuition and fees (Policy 3) incurs the highest cost compared to the other policies. In simpler terms, the most impactful policy experiment is the most expensive among the options considered.

Policy comparisons based on Efficiency measures

Another method for exploring pertinent cost and benefit comparisons involves examining alterations in the present value of lifetime earnings among college students. This analysis would entail comparing adjustments in the financial aid program between the policy experiment and the benchmark economy. This selection of measurement is influenced by the research conducted by Caponi (2011), which highlights the effectiveness of policies promoting immigrant assimilation by focusing on individuals with higher education. The author uses a structural approach to estimate the skill distribution of Mexican immigrants into the United States. He finds that immigrants face a significant loss of capacity to translate their abilities into earnings. Therefore, assimilation policies such as increasing their language skills or promoting these immigrants' understanding of the host country's routines have a more significant positive effect on the first and second-generation earnings if the assimilation programs focus on college-educated immigrants rather than the high school-educated ones.

The subsequent equation elucidates how I incorporated policy experiment effects on college students' present value of lifetime earnings,

$$\text{Gain in income per dollar} \equiv \frac{\text{Net gain in the present value of college students lifetime earnings}}{\text{Net policy experiment cost}}.$$

The numerator represents the present value of college students' total earnings within the policy experiment context, adjusted for the present value of their total earnings compared to the benchmark economy. Correspondingly, the denominator corresponds to the overall financial expenditure (including merit- and need-based grants and tuition subsidies) within the new policy experiment framework, subtracted by the financial outlay within the benchmark economy.

Table 3.8 offers valuable insights into the efficiency of financial aid policies, presenting a ranking determined by the increase in the present value of income per dollar cost resulting from alterations in the financial assistance policy. The most efficient experiment involves expanding the maximum scholarship threshold to individuals with medium abilities who qualify for merit-based scholarships within the benchmark economy. Should policymakers

Table 3.8: College students gain in income per dollar of increase in financial aid costs

Policy experiments	Gain ($)
Policy 1_maxAid_expansion	5.2
Policy 1_eligibility_maxAid_expansions	4.7
Policy 1_eligibility_expansion	4.5
Policy 2_eligibility_expansion	4.3
Policy 2_maxAid_expansion	3.3
Policy 2_eligibility_maxAid_expansions	3.2
Policy 3	3.1
Policy 2	2.8
Policy 1	2.2

Policy 1 = 30% increase in merit-based scholarships,
Policy 1_maxAid_expansion = Coverage expansion in the merit-based scholarship maximum amount,
Policy 1_eligibility_maxAid_expansions = Coverage expansion in the merit-based scholarship maximum amount and the lowest ability threshold,
Policy 1_eligibility_expansion = Coverage expansion in the merit-based scholarship lowest ability threshold,
Policy 2 = 30% increase in need-based grants,
Policy 2_maxAid_expansion = Coverage expansion in the need-based grant maximum amount,
Policy 2_eligibility_maxAid_expansions = Coverage expansion in the need-based grant maximum amount and the highest initial-asset threshold,
Policy 2_eligibility_expansion = Coverage expansion in the need-based grant highest initial-asset threshold,
Policy 3 = 30% decrease in tuition and fees,
Policy 4 (35% increase in student loan limit) is not in the table because the cost calculation of the financial aid policies is based on merit-based scholarships and need-based grants.

opt for this experiment, each additional dollar in total financial aid yields a 5.2-dollar increase in the present value of lifetime earnings for college students. Nevertheless, this approach demonstrates limited effectiveness in attracting new college students. This policy only increases the college enrollments by 2.7 percentage points.

Upon comparing Tables 3.6 to 3.8, it becomes evident that policies with higher levels of generosity do not always translate to superior efficiency. Intriguingly, Policy 3, the experiment yielding the most impactful outcomes, ranks relatively lower on the efficiency scale. This policy entails a uniform 30% reduction in tuition and fees across all students, irrespective of their abilities or financial circumstances. This finding implies that specific effective policies might incur substantial costs that outweigh the benefits gained in enrollment, thus diminishing their efficiency in accomplishing their intended objectives.

Conversely, policies that expand financial aid while strategically directing their focus towards specific subsets of individuals based on ability or initial assets emerge as the most productive options, balancing a harmonious balance between effectiveness in boosting college enrollment and the accompanying expenses. To be more precise, Table 3.8 illustrates that policies targeting individuals with higher abilities stand out as the most efficient. Since the new students will accumulate more human capital and enjoy the higher skill prices during the life cycle, their present value of lifetime earnings surpasses what they would have attained following a non-collegiate trajectory in the benchmark economy.

Among the most efficient experiments, the one that broadens the scope of scholarship eligibility and extends the coverage of the maximum merit-based financial aid (Policy 1_eligibility_maxAid_expansions) is an experiment with both high effectiveness and efficiency in attracting new college students. This experiment not only exhibits remarkable effectiveness but also excels in terms of efficiency when it comes to attracting new college students. Furthermore, Policy 1_maxAid_expansion, centred on broadening the coverage of full merit-based scholarship distribution for individuals already qualified to receive such scholarships, emerges as the most efficient strategy for augmenting college enrollments. By maintaining the same eligibility threshold and strategically targeting individuals with higher learning abilities, this Policy maximizes its impact on increasing college enrollments while ensuring the efficient use of resources. By focusing on policies that are both effective and efficient, policymakers can provide the optimal allocation of resources to expand college access and foster educational opportunities for a broader segment of the population.

3.9 Summary and conclusion

I comprehensively analyzed the determinants of college and college major choices in this chapter using a partial equilibrium heterogeneous agent life cycle model. These experiments are compared based on their effectiveness in raising enrollments and their cost efficiencies.

The distributions of initial endowments in the model reveal essential insights into the decision-making process of individuals regarding college enrollment and career choices. College students, on average, exhibit a higher learning ability than no-college individuals at the time of decision-making, indicating a *comparative advantage* in learning ability for the former group. This comparative advantage in ability allows college students to accumulate a higher stock of human capital over their life cycle. The higher level of accumulated human capital and the higher skill prices result in higher wages, earnings, and consumption levels for college-type individuals.

More specifically, STEM individuals possess higher learning abilities and skill prices than all individuals. Due to their higher wages, STEM individuals generally work more but reduce the burden of working towards the end of their working periods. ARTS have a lower level of initial human capital compared to no-college individuals. However, thanks to their relatively higher ability and skill prices, they invest and accumulate more and enjoy a higher level of consumption during the life cycle.

The simulation of the model enables the evaluation of ten policy experiments, each designed to impact college enrollment and career choices. These policies include a 30% increase in merit-based scholarships, a 30% increase in need-based grants, a 30% decrease in tuition and fees, a 35% rise in the student loan limit, and six coverage expansions in financial aid: three in merit-based scholarships and three in need-based grants.

Among these policies, the reduction in tuition and fees stands out as the most effective in increasing college enrollment. This non-targeted policy leads to significant positive outcomes for college enrollment, regardless of specific abilities or asset levels. However, to ensure a consistent policy comparison, it is essential to consider each policy's cost efficiency by evaluating its effect on increasing the present value of lifetime earnings of college students. This comprehensive cost and benefit analysis shows that the most efficient experiments are tailoring financial aid to specific subsets of individuals based on their abilities and initial assets. The financial aid policies that prove most efficient involve the experiments that expand the maximum amount of merit-based grants and extend the ability threshold to receive scholarships.

The results of the various experiments presented in the policy analysis section of this chapter offer valuable insights for achieving desired objectives through different policy approaches. However, choosing the most appropriate policy depends on policymakers' goals and priorities. By carefully considering each policy's effectiveness and cost efficiency, policymakers can make well-informed decisions that align with their specific objectives in promoting higher education and college enrollment.

Summary

The cost of college education has increased significantly over the years, with the average public four-year college tuition and fees being 2.58 times higher in 2021-22 compared to 1991-92 after adjusting for inflation. This rising cost has put a considerable financial burden on students and their families. In the meantime, various financial aid forms have been introduced, including loans, need-based grants, merit-based scholarships, and tuition fee discounts to make college education more accessible. This financial assistance has played a crucial role in helping many low- and middle-income students pursue higher education.

The main objectives of this dissertation are to investigate the determinants of college enrollment and understand the factors that influence students' choices between STEM and ARTS majors. Additionally, the study aims to evaluate the effectiveness and efficiency of various financial aid policies in increasing college, STEM, and ARTS enrollments. The research seeks to answer questions such as: What factors influence individuals' decisions to attend college? Which financial aid policies effectively increase college, STEM, and ARTS enrollments? Among the practical approaches, which policies are the most efficient in achieving higher enrollments at the same level of financing cost?

Chapter 1 provides a comprehensive review of the existing education literature, specifically focusing on college enrollment and major choices. The chapter categorizes various strands in educational literature and discusses their findings to shed light on the research questions. The review begins with reduced-form models that explore the relationship

between wages and schooling. Next, the chapter delves into structural models, such as Ben-Porath and Roy's self-selection models. These models provide a deeper understanding of the decision-making process for individuals when choosing between different educational paths and majors.

The chapter also covers Discrete Choice Dynamic Programming (DCDP) and multi-stage learning literature. These models capture the sequential decision-making process of individuals over time, considering their evolving information and preferences. DCDP models are particularly relevant in understanding the dynamic aspects of educational and occupational choices. Furthermore, the literature survey explores the framework of subjective expectations data. This approach involves gathering data on individuals' expectations regarding various outcomes, such as educational choices, earnings, and labour supply.

Furthermore, this chapter introduces the literature investigating the historical evolution of educational choices in the United States over the past decades. They explain this evolution using various factors such as the introduction of standardized test scores, changes in the mean ability of cohorts, and variations in the tuition, education quality, and taste of individuals for schooling. This chapter continues by categorizing the literature investigating the determinants of college or college major choices: the monetary and non-monetary factors. In the end, it explains various literature related to educational policies and the results of these policy experiments.

Chapter 2 focuses on the data used to calibrate the model developed in Chapter 3. The primary dataset used is the Panel Study of Income Dynamics (PSID), which provides valuable information for deriving the relevant statistics necessary for model fitting and estimating human capital accumulation function parameters. The PSID dataset allows researchers to estimate various model parameters directly from real-world observations. Some model parameters, such as the federal loan limit, total costs of a four-year college, tuition and fees, interest rates on student loans, growth rates of skill prices, and human capital depreciation rate, are calibrated using the information from the PSID dataset. Other parameters of my model are the mean and standard deviations of the joint distribution of initial endowments of the economy: ability, initial human capital, and assets. These nine parameters are jointly calibrated by minimizing the distance between the life cycle income statistics (mean, mean/median, and Gini coefficients) derived from the PSID dataset and model moments developed in Chapter 3.

In Chapter 3, I present a quantitative theory of college education, focusing on two major fields of study: STEM and ARTS. The model captures agents' decision-making process from various options, including investment in goods, time allocation to human capital accumulation, working time, and the level of human capital accumulated over time. The model's core lies in maximizing agents' objective functions, which guide their choices among three career paths: attending college (either in STEM or ARTS) or directly entering the job market after graduating high school. The model considers various sources of financing for college costs, including family contributions, merit-based scholarships, need-based grants, federal student loans, and earnings from working while studying in college.

My research is influenced by Ionescu (2009), which highlights the role of college education in transforming high school-type human capital into another class that commands a higher skill price in the labour market after college graduation. This transformation allows individuals to acquire more valuable human capital associated with a higher depreciation rate. As a result, college studies require a higher level of learning ability to compensate for the higher rates of human capital depreciation.

However, my model introduces several crucial distinctions from Ionescu's work. First, it incorporates two distinct fields of study, namely STEM and ARTS, recognizing individuals' diverse educational pursuits. Second, I have expanded the agent's objective function to include work and investment time in human capital, which Ionescu's original model did not present. While Ionescu's model only considered consumption as the sole component, my model considers a more comprehensive set of factors to better represent the complexities of decision-making in this context. Third, the model has two distinct, well-defined functional forms for merit- and need-based financial aid programs and fourth, the model applies two conditions as proxies for college graduation. They are a minimum time invested in human capital and thresholds as the minimum increase in the initial human capital endowment during college studies for STEM and ARTS.

Furthermore, I modified the model to capture real-world phenomena better and ensure its results align with available data and empirical observations. First, my model relaxes the assumption of borrowing constraints, allowing agents to freely save and borrow during their working periods in the life cycle. This feature reflects a more flexible and realistic approach to individuals' financial decisions, as they can strategically manage their savings and borrowing to achieve their educational and career goals. Second, I incorporated retirement into the model based on several considerations. Retirement introduces a motive for saving, as individuals need to accumulate enough financial resources to sustain their desired standard of living during their retirement. Also, it impacts agents' consumption behaviour within the model. As individuals transition from working to retirement, their income streams change, and they adjust by smoothing their consumption patterns accordingly. Third, students can work at "student jobs" while studying during college. Finally, in defining the distribution of the initial economy, I extended the number of parameters to be calibrated endogenously from five to nine parameters.

Results of the benchmark model confirm the notion of *comparative advantage*. Those with higher learning abilities (in acquiring human capital) choose the college path. Also, the results show that ability is vital in accumulating human capital during the life cycle. None of the low-ability individuals pursue college studies due to higher college-type human capital depreciation rates. Also, on average, STEM students have a combination of higher abilities, higher initial human capital, and higher initial assets than ARTS.

An exciting finding in policy experiments is for the individuals from low-asset families with moderate ability levels endowed with a lower level of initial human capital. These individuals may have low earning potential in the benchmark economy due to their lower initial human capital. Also, they lack financial resources, which can hinder their college attendance despite their medium ability level. The policy experiments targeting low-asset families have a transformative impact on these individuals' lives. By providing need-based grants and expanding financial aid coverage, these policies enable them to access a college education, invest in human capital accumulation, boost their earning potential and change their trajectory significantly.

To summarize, my research explores the impact of various policy experiments on educational decisions, particularly regarding college enrollment and major selection. I have uncovered essential insights by applying these policies to the benchmark economy. Among the policy experiments, a 30% decrease in tuition and fees emerges as the most effective policy to increase overall college enrollment, particularly for students pursuing ARTS majors. However, this policy's efficiency level is relatively low, as it provides free financial assistance to all potential students across different ability and initial asset levels. In contrast, policies that strategically target specific subgroups of individuals and concurrently expand the maximum financial aid amount or extend eligibility thresholds emerge as the most efficient. These policies achieve a reasonable level of effectiveness in increasing college enrollments while targeting specific groups already eligible for financial aid based on their ability or initial asset levels.

My model's predictions demonstrate the trade-offs between effectiveness and efficiency in implementing different educational policies. Policymakers must consider both factors when designing policies to increase college enrollment and improve access to education for various student populations. By identifying the most effective and efficient policies, my research provides valuable insights for policymakers seeking to achieve their desired objectives in college education and beyond. This dissertation lays a solid foundation by developing a quantitative model and using comprehensive longitudinal sample data to investigate college enrollment and educational decisions. The model's richness and the data-driven calibration offer valuable insights into the dynamics of college education and the impact of various policies. The potential extension to this research could be introducing other model features, such as multi-dimensional learning abilities, college dropouts, separating public and private colleges, different forms of the human capital production function for formal college study and working periods, different retirement ages across careers, bequest motive, and non-pecuniary benefits of schooling.

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Appendices

Appendix A

The PSID occupation codes

Census codes 2010 for occupations - STEM category:

0110 Computer and information systems managers

0300 Architectural and engineering managers

0350 Medical and health services managers

0360 Natural sciences managers

1005 Computer and information research scientists

1006 Computer systems analysts

1007 Information security analysts

1010 Computer programmers

1020 Software developers, applications and systems software

1030 Web developers

1050 Computer support specialists

1060 Database administrators

1105 Network and computer systems administrators

1106 Computer network architects

1107 Computer occupations, all other

1200 Actuaries

1210 Mathematicians

1220 Operations research analysts

1230 Statisticians

1240 Miscellaneous mathematical science occupations

1300 Architects, except naval

1310 Surveyors, cartographers, and photogrammetrists

1320 Aerospace engineers

1330 Agricultural engineers

1340 Biomedical engineers

1350 Chemical engineers

1360 Civil engineers

1400 Computer hardware engineers

1410 Electrical and electronics engineers

1420 Environmental engineers

1430 Industrial engineers, including health and safety

1440 Marine engineers and naval architects

1450 Materials engineers

1460 Mechanical engineers

1500 Mining and geological engineers, including mining safety engineers

1510 Nuclear engineers

1520 Petroleum engineers

1530 Engineers, all other

1540 Drafters

1550 Engineering technicians, except drafters

1560 Surveying and mapping technicians

1600 Agricultural and food scientists

1610 Biological scientists

1640 Conservation scientists and foresters

1650 Medical scientists

1660 Life scientists, all other

1700 Astronomers and Physicists

1710 Atmospheric and space scientists

1720 Chemists and materials scientists

1740 Environmental scientists and geoscientists

1760 Physical scientists, all other

1800 Economists

1815 Survey researchers

1820 Psychologists

1830 Sociologists

1840 Urban and regional planners

1860 Miscellaneous social scientists and related workers

1900 Agricultural and food science technicians

1910 Biological technicians

1920 Chemical technicians

1930 Geological and petroleum technicians

1940 Nuclear technicians

1950 Social science research assistants

1965 Miscellaneous life, physical, and social science technicians

3000 Chiropractors

3010 Dentists

3030 Dietitians and nutritionists

3040 Optometrists

3050 Pharmacists

3060 Physicians and surgeons

3110 Physician assistants

3120 Podiatrists

3140 Audiologists

3150 Occupational therapists

3160 Physical therapists

3200 Radiation therapists

3210 Recreational therapists

3220 Respiratory therapists

3230 Speech-language pathologists

3235 Exercise physiologists

3245 Therapists, all other

3250 Veterinarians

3255 Registered nurses

3256 Nurse anesthetists

3257 Nurse midwives

3258 Nurse practitioners

3260 Health diagnosing and treating practitioners, all other

3300 Clinical laboratory technologists and technicians

3310 Dental hygienists

3320 Diagnostic Related Technologists and technicians

3400 Emergency medical technicians and paramedics

3420 Health practitioner support technologists and technicians

3500 Licensed practical and licensed vocational nurses

3510 Medical records and health information technicians

3520 Opticians, dispensing

3535 Miscellaneous health technologists and technicians

3540 Other healthcare practitioners and technical occupations

4930 Sales engineers

Census codes 2010 for occupations - ARTS category:

2000 Counselors

2010 Social workers

2015 Probation officers and correctional treatment specialists

2016 Social and human service assistants

2025 Miscellaneous community and social service specialists, including health educators and community health workers

2040 Clergy

2050 Directors, religious activities and education

2060 Religious workers, all other

2200 postsecondary teachers

2300 Preschool and kindergarten teachers

2310 Elementary and middle school teachers

2320 Secondary school teachers

2330 Special education teachers

2340 Other teachers and instructors

2400 Archivists, curators, and museum technicians

2430 Librarians

2440 Library technicians

2540 Teacher assistants

2550 Other education, training, and library workers

2600 Artists and related workers

2630 Designers

2700 Actors

2710 Producers and directors

2740 Dancers and choreographers

2750 Musicians, singers, and related workers

2760 Entertainers and performers, sports and related workers, all other

2800 Announcers

2810 News analysts, reporters and correspondents

2825 Public relations specialists

2830 Editors

2840 Technical writers

2850 Writers and authors

2860 Miscellaneous media and communication workers

2900 Broadcast and sound engineering technicians and radio operators

2910 Photographers

2920 Television, video, and motion picture camera operators and editors

2960 Media and communication equipment workers, all other

Census codes 2010 for occupations - Business and Finance category:

0500 Agents and business managers of artists, performers, and athletes

0510 Buyers and purchasing agents, farm products

0520 Wholesale and retail buyers, except farm products

0530 Purchasing agents, except wholesale, retail, and farm products

0540 Claims adjusters, appraisers, examiners, and investigators

0565 Compliance Officers

0600 Cost Estimators

0630 Human resources workers

0640 Compensation, benefits, and job analysis specialists

0650 Training and development specialists

0700 Logisticians

0710 Management analysts

0725 Meeting, convention, and event planners

0726 Fundraisers

0735 Market research analysts and marketing specialists

0740 Business operations specialists, all other

0800 Accountants and auditors

0810 Appraisers and assessors of real estate

0820 Budget analysts

0830 Credit analysts

0840 Financial analysts

0850 Personal financial advisors

0860 Insurance underwriters

0900 Financial examiners

0910 Credit counsellors and loan officers

0930 Tax examiners and collectors, and revenue agents

0940 Tax preparers

0950 Financial specialists, all other

Census codes 2010 for occupations - Law category:

2100 Lawyers

2105 Judicial law clerks

2110 Judges, magistrates, and other judicial workers

2145 Paralegals and legal assistants

2160 Miscellaneous legal support Workers

Census codes 2010 for occupations - Sports category:

2720 Athletes, coaches, umpires, and related workers

Census codes 2000 for occupations - STEM category:

011 Computer and information systems managers

030 Engineering managers

035 Medical and Health Services managers

036 Natural sciences managers

100 Computer scientists and systems analysts

101 Computer programmers

102 Computer software engineers

104 Computer support specialists

106 Database administrators

110 Network and computer systems administrators

111 Network systems and data communications analysts

120 Actuaries

121 Mathematicians

122 Operations research analysts

123 Statisticians

124 Miscellaneous mathematical science occupations

130 Architects, except naval

131 Surveyors, cartographers, and photogrammetrists

132 Aerospace engineers

133 Agricultural engineers

134 Biomedical engineers

135 Chemical engineers

136 Civil engineers

140 Computer hardware engineers

141 Electrical and electronics engineers

142 Environmental engineers

143 Industrial engineers, including health and safety

144 Marine engineers and naval architects

145 Materials engineers

146 Mechanical engineers

150 Mining and geological engineers, including mining safety engineers

151 Nuclear engineers

152 Petroleum engineers

153 Engineers, all other

154 Drafters

155 Engineering technicians, except drafters

156 Surveying and mapping technicians

160 Agricultural and food scientists

161 Biological scientists

164 Conservation scientists and foresters

165 Medical scientists

170 Astronomers and physicists

171 Atmospheric and space scientists

172 Chemists and materials scientists

174 Environmental scientists and geoscientists

176 Physical scientists, all other

180 Economists

181 Market and survey researchers

182 Psychologists

183 Sociologists

184 Urban and regional planners

186 Miscellaneous social scientists and related workers

190 Agricultural and food science technicians

191 Biological technicians

192 Chemical technicians

193 Geological and petroleum technicians

194 Nuclear technicians

196 Other Life, physical, and social science technicians

300 Chiropractors

301 Dentists

303 Dietitians and nutritionists

304 Optometrists

305 Pharmacists

306 Physicians and surgeons

311 Physician assistants

312 Podiatrists

313 Registered nurses

314 Audiologists

315 Occupational therapists

316 Physical therapists

320 Radiation therapists

321 Recreational therapists

322 Respiratory therapists

323 Speech-Language pathologists

324 Therapists, all other

325 Veterinarians

326 Health diagnosing and treating practitioners, all other

330 Clinical laboratory technologists and technicians

331 Dental hygienists

332 Diagnostic-related technologists and technicians

340 Emergency medical technicians and paramedics

341 Health diagnosing and treating practitioner support technicians

350 Licensed practical and licensed vocational nurses

351 Medical records and health information technicians

352 Opticians, dispensing

353 Miscellaneous health technologists and technicians

354 Other healthcare practitioners and technical occupations

493 Sales engineers

Census codes 2000 for occupations - ARTS category:

200 Counselors

201 Social workers

202 Miscellaneous community and social service specialists

204 Clergy

205 Directors, religious activities and education

206 Religious workers, all other

220 postsecondary teachers

230 Preschool and kindergarten teachers

231 Elementary and middle school teachers

232 Secondary school teachers

233 Special education teachers

234 Other teachers and instructors

240 Archivists, curators, and museum technicians

243 Librarians

244 Library technicians

254 Teacher assistants

255 Other education, training, and library workers

260 Artists and related workers

263 Designers

270 Actors

271 Producers and directors

274 Dancers and choreographers

275 Musicians, singers, and related workers

276 Entertainers and performances

280 Announcers

281 News analysts, reporters and correspondents

282 Public relations specialists

283 Editors

284 Technical writers

285 Writers and authors

286 Miscellaneous media and communication workers

290 Broadcast and sound engineering technicians and radio operators

291 Photographers

292 Television, video, and motion picture camera operators and editors

296 Media and communication equipment workers, all other

Census codes 2000 for occupations - Business and Finance category:

050 Agents and business managers of artists, performers, and athletes

051 Purchasing agents and buyers, farm products

052 Wholesale and retail buyers, except farm products

053 Purchasing agents, except wholesale, retail, and farm products

054 Claims adjusters, appraisers, examiners, and investigators

056 Compliance officers, except agriculture, Construction, health and safety, and transportation

060 Cost estimators

070 Logisticians

071 Management analysts

072 Meeting and convention planners

073 Other business operations specialists

080 Accountants and auditors

081 Appraisers and assessors of real estate

082 Budget analysts

083 Credit analysts

084 Financial analysts

085 Personal financial advisors

086 Insurance underwriters

090 Financial examiners

091 Loan counsellors and officers

093 Tax examiners, collectors, and revenue agents

094 Tax preparers

095 Financial specialists, all other

Census codes 2000 for occupations - Law category:

210 Lawyers

211 Judges, magistrates, and other judicial workers

214 Paralegals and legal assistants

215 Miscellaneous legal support workers

Census codes 2000 for occupations - Sports category:

272 Athletes, coaches, umpires, and related workers

Census codes 1970 for occupations - STEM category:

002 Architects

003 Computer programmers

004 Computer systems analysts

005 Computer specialists, n.e.c.

006 Aeronautical astronautical engineers

010 Chemical engineers

011 Civil engineers

012 Electrical and electronic engineers

013 Industrial engineers

014 Mechanical engineers

015 Metallurgical and materials engineers

020 Mining engineers

021 Petroleum engineers

022 Sales engineers

023 Engineers, n.e.c.

034 Actuaries

035 Mathematicians

036 Statisticians

042 Agricultural scientists

043 Atmospheric and space scientists

044 Biological scientists

045 Chemists

051 Geologists

052 Marine scientists

053 Physicists and astronomers

054 Life and Physical scientists, n.e.c.

055 Operations and systems researchers and analysts

056 Personnel and labour relations workers

061 Chiropractors

062 Dentists

063 Optometrists

064 Pharmacists

065 Physicians, including osteopaths

071 Podiatrists

072 Veterinarians

073 Health practitioners, n.e.c.

074 Dieticians

075 Registered nurses

076 Therapists

081 Dental hygienists

082 Health record technologists and technicians

083 Radiologic technologists and technicians

085 Health technologists and technicians, n.e.c.

091 Economists

092 Political scientists

093 Psychologists

094 Sociologists

095 Urban and regional planners
096 Social scientists, n.e.c.
102 Agriculture teachers 103 Atmospheric, earth, marine, and space teachers
104 Biology teachers
105 Chemistry teachers
110 Physics teachers
111 Engineering teachers
112 Mathematics teachers
113 Health specialists teachers
114 Psychology teachers
116 Economics teachers
121 Sociology teachers
122 Social science teachers, n.e.c.
131 Home economics teachers
134 Trade, industrial, and technical teachers
150 Agriculture and biological technicians, except health
151 Chemical technicians
152 Draftsmen
153 Electrical and electronic engineering technicians
154 Industrial engineering technicians
155 Mechanical engineering technicians
156 Mathematical technicians
161 Surveyors
162 Engineering and science technicians, n.e.c.

Census codes 1970 for occupations - ARTS category:

032 Librarians
033 Archivists and curators
086 Clergymen
090 Religious workers, n.e.c.
100 Social workers
120 History teachers
123 Art, drama, and music teachers
125 Education teachers
126 English teachers
130 Foreign language teachers
135 Miscellaneous teachers, college and university
140 Teachers, college and university, the subject not specified
141 Adult education teachers
142 Elementary school teachers
143 Pre-kindergarten and kindergarten teachers
144 Secondary school teachers
145 Teachers, except college and university, n.e.c.
175 Actors
181 Authors
182 Dancers
183 Designers
184 Editors and reporters

185 Musicians and composers

190 Painters and sculptors

191 Photographers

192 Public relations men and publicity writers

193 Radio and television announcers

194 Writers, artists, and entertainers, n.e.c.

Census codes 1970 for occupations - Business and Finance category:

001 Accountants

115 Business and commerce teachers

203 Buyers and shippers, farm products

205 Buyers, wholesale and retail trade

210 Credit Men

Census codes 1970 for occupations - Law category:

030 Judges

031 Lawyers

132 Law teachers

Census codes 1970 for occupations - Sports category:

180 Athletes and kindred workers

Field variable codes - STEM category:

03 Technician (medical); recording engineer; "electronics"; nuclear technician

11 Computer programming

12 "Computer," n.e.c.

17 Engineering; electrical, mechanical, etc.

Field variable codes - ARTS category:

16 Advertising; photography

18 Art; music; drama; dance

19 Foreign language

20 Religion

Appendix B

Some papers in detail

B.1 Mincer (1974)

The author defines h_t as the potential human capital embedded in individual at time t:

$$h_t = h_{t-1} + rc_{t-1}. \tag{46}$$

Investment in human capital is expressed as a ratio of investment expenditures over potential earnings,

$$k_t = \frac{c_t}{h_t} = \begin{cases} 1 & \text{during schooling,} \\ < 1 & \text{after schooling.} \end{cases} \tag{47}$$

The following shows the manipulating of the potential earnings equation, $h_t = h_{t-1} + rc_{t-1}$, to reach an equation showing its logarithm in terms of years of schooling and work experience. From Equation (47), I can write $c_{t-1} = k_{t-1}h_{t-1}$ and insert into potential earnings formula ($h_t = h_{t-1} + rc_{t-1}$). It gives $h_t = h_{t-1}(1 + rk_{t-1})$ which could be written recursively as

$$h_t = h_0(1 + rk_0)(1 + rk_1)\ldots(1 + rk_{t-1}). \tag{48}$$

Using the concise form of multiplication changes Equation (48) into

$$h_t = h_0 \ \Pi_{j=0}^{t-1}((1 + rk_j) \text{ where } k_0 = 0, \tag{49}$$

and taking logarithm from both sides of Equation (49) gives the following equation

$$\ln h_t = \ln h_0 + \sum_{j=0}^{t-1} \ln(1 + rk_j). \tag{50}$$

Then, substituting $rk_j \approx \ln(1 + rk_j)$ into Equation (50) and taking r out of summation results in

$$\ln h_t \approx \ln h_0 + r \sum_{j=0}^{t-1} k_j, \tag{51}$$

where h_0 is the initial human capital or the initial earning capacity. It is exogenous and would be an individual's earnings without any subsequent investment in human capital. Equation (52) is obtained by separating school periods (s) from post-schooling periods (p)

$$\ln h_t \approx \ln h_0 + \underbrace{r_s \sum_{i=0}^{s} k_i}_{\substack{\text{investment in skills} \\ \text{during school periods}}} + \underbrace{r_p \sum_{j=s+1}^{t-1} k_j}_{\substack{\text{post-schooling investments} \\ \text{in human capital}}}. \tag{52}$$

Where s is the total years of schooling, r_s is the average rate of return across all schooling investments, and r_p is the average rate across post-schooling training investments. During school $k_i = 1$, therefore Equation (52) could be written as

$$\ln h_t \approx \ln h_0 + r_s \ s + r_p \sum_{j=s+1}^{t-1} k_j. \tag{53}$$

Equation (53) contains the years of schooling (s), but it does not show the years of "work experience". The following assumption helps to introduce the work experience and develop the equation.

Key assumption

The rate of post-school investment in human capital accumulation linearly declines over time,

$$k_t = \kappa(1 - \frac{x}{n}), \quad \text{where } x = (t - s) \geq 0. \tag{54}$$

Equation (54) introduces a relationship between the rate of investment in human capital during working periods (k_t) and the years of work experience (x). κ represents the investment ratio in the first year of working life, t is the current age, s is the number of years of schooling, and n is the length of working life. This relationship shows that at the first year of working life ($x = 0$), the investment ratio equals κ, and at the end of working life ($x = n$), the investment ratio becomes zero.

Using this assumption and substituting $k_j = \kappa(1 - \frac{j-s}{n})$ and $t = s + x$, helps to rewrite Equation (53) as the relationship between potential earnings, schooling, and experience,

$$\ln h_{s+x} \approx \ln h_0 + r_s s + r_p \sum_{j=s+1}^{(s+x)-1} \kappa(1 - \frac{j-s}{n}).$$

Expanding the summation and further manipulation of the terms inside the bracket on the right-hand side delivers the following equations

$$\ln h_{s+x} \approx \ln h_0 + r_s s + r_p \left[\kappa(1 - \frac{1}{n}) + \kappa(1 - \frac{2}{n}) + \ldots + \kappa(1 - \frac{x-1}{n})\right],$$
$$\ln h_{s+x} \approx \ln h_0 + r_s s + r_p \left[(x-1)\kappa - \frac{\kappa}{n}\Big(1 + 2 + \ldots + (x-1)\Big)\right],$$
$$\ln h_{s+x} \approx \ln h_0 + r_s s + r_p \left[-\kappa + \kappa x - \frac{\kappa}{n}\Big(\frac{(x-1)x}{2}\Big)\right],$$

$$\ln h_{s+x} \approx [\ln h_0 - \kappa r_p] + r_s s + \left[\kappa r_p + \frac{\kappa r_p}{2n}\right] x - \left[\frac{\kappa r_p}{2n}\right] x^2. \tag{55}$$

Equation (55) shows that potential log earnings are linear in years of schooling and linear and quadratic in years of experience. However, to reach actual (observed) earnings, y_t, the investment costs, c_t, need to be subtracted from the potential earnings, h_t,

$$y_t = h_t - c_t = h_t - k_t h_t = h_t(1 - k_t). \tag{56}$$

Using the key assumption of the model, $k_t = \kappa(1 - \frac{x}{n})$, Equation (56) could be written as

$$y_{s,x} = hs, x\left[1 - \kappa(1 - \frac{x}{n})\right].$$

Taking logarithms from both sides delivers

$$\ln y_{s,x} = \ln hs, x - \ln\left[1 - \kappa(1 - \frac{x}{n})\right],$$

and substituting $\kappa(1 - \frac{x}{n}) \approx \ln\left[1 - \kappa(1 - \frac{x}{n})\right]$ in the above equation, results in

$$\ln y_{s,x} \approx \ln h_{s,x} - \kappa(1 - \frac{x}{n}). \tag{57}$$

Substituting Equation (55) into Equation (57) and rearranging it helps to find Equation (58) representing the logarithm of actual earnings as a function of years of schooling and experience

$$\ln y_{s,x} \approx \underbrace{[\ln h_0 - \kappa r_p - \kappa]}_{\beta_0} + \underbrace{r_s}_{\beta_1} s + \underbrace{\left[\kappa r_p + \frac{\kappa r_p}{2n} + \frac{\kappa}{n}\right]}_{\beta_2} x - \underbrace{\left[\frac{\kappa r_p}{2n}\right]}_{\beta_3} x^2,$$

$$\ln y_{s,x} \approx \beta_0 + \beta_1 s + \beta_2 x - \beta_3 x^2. \tag{58}$$

Equation (58) could be written as a regression model

$$\ln y = \beta_0 + \beta_1 s + \beta_2 x - \beta_3 x^2 + \varepsilon. \tag{59}$$

Equation (59) is *the popular Mincer wage equation*. y is a measure of income or wage rates as a function of completed years of schooling (s) and the number of years an individual has worked since schooling (x).[1] Using Equation (4) as a regression model requires data on wages or annual earnings for full-time workers because the model assumes y as the potential earning (net of investment cost) when an individual works full time. Therefore, in using annual earnings, it is much preferred to use data on individuals who have been full-time in

[1] The labour market experience is usually approximated by potential labour market experience: age minus six (age at the start of compulsory schooling) minus years of attained schooling.

the labour market and not the part-time ones (Griliches, 1977).

The error term, ε, is a mean zero residual with $\mathbb{E}(\varepsilon|s,x) = 0$, and the coefficient β_1 shows how much average earnings increases with schooling (*ex-post* average growth rate of earnings with schooling). The coefficient on schooling, β_1, is known as "*Mincer coefficient*."

B.2 Ben-Porath (1967)

Obtaining optimal human capital investments requires equating both the marginal benefit and the marginal cost of producing human capital. Finding these values needs to solve the agent's problem. Given initial human capital, h_0, individuals maximize the present value of their disposable income over the life cycle ending at time T, which is assumed to be the end of their life,

$$\int_0^T e^{-rt}\Big\{wh(t) - c(t)\Big\}dt = \int_0^T e^{-rt}\Big\{wh(t)\Big(1 - s(t)\Big) - p_d d(t)\Big\}dt, \tag{60}$$

subject to Equations (61) to (63),

$$\dot{h}(t) = \overbrace{f\Big(s(t), h(t), d(t)\Big)}^{q(t)} - \delta h(t), \tag{61}$$

$$q(t) = a\Big(s(t)h(t)\Big)^{\alpha} d(t)^{\beta}, \tag{62}$$

$$0 \leq s(t) \leq 1. \tag{63}$$

The problem mentioned in Equation (60) can be solved by setting up the present value Hamiltonian,

$$\begin{aligned}\mathcal{H}\Big(h(t), s(t), d(t), \mu(t), t\Big) = e^{-rt}\Big\{wh(t)\Big(1 - s(t)\Big) - p_d d(t)\Big\} + \mu(t)\Big\{a\Big(s(t)h(t)\Big)^{\alpha} d(t)^{\beta} - \delta h(t)\Big\} \\ + \lambda_1(t)\Big(1 - s(t)\Big) + \lambda_2(t)s(t),\end{aligned}$$

with transversality condition $\mu(T)h(T) = 0$. The necessary conditions for this problem are

$$\frac{\partial \mathcal{H}}{\partial s} = 0: \qquad e^{-rt}wh(t) = \mu(t)\alpha a s(t)^{\alpha-1}h(t)^{\alpha}d(t)^{\beta} - \lambda_1(t) + \lambda_2(t), \tag{64}$$

$$\frac{\partial \mathcal{H}}{\partial d} = 0: \qquad e^{-rt}p_d = \mu(t)\beta a s(t)^{\alpha}h(t)^{\alpha}d(t)^{\beta-1}, \tag{65}$$

$$\frac{\partial \mathcal{H}}{\partial h} = -\dot{\mu}(t): \qquad e^{-rt}w\Big[1 - s(t)\Big] + \mu(t)\Big(\alpha a s(t)^{\alpha}h(t)^{\alpha-1}d(t)^{\beta} - \delta\Big) = -\dot{\mu}(t), \tag{66}$$

and $\lambda_1(t)\Big(1-s(t)\Big) = 0$, $\lambda_2(t)s(t) = 0$, with $\lambda_1(t) \geq 0$ and $\lambda_2(t) \geq 0$, $\lambda_1(t) \geq 0$ and $\lambda_2(t) = 0$, if $s(t) = 1$, $\lambda_1(t) = 0$ and $\lambda_2(t) \geq 0$, if $s(t) = 0$, and $\lambda_1(t) = \lambda_2(t) = 0$ if $s(t) \in (0, 1)$.

Assuming an interior solution for $s(t)$, that is for $s(t) \in (0, 1)$, Equation (64) can be written as

$$e^{-rt}ws(t) = \mu(t)\alpha a s(t)^{\alpha}h(t)^{\alpha-1}d(t)^{\beta}. \tag{67}$$

Substituting Equation (67) into Equation (66) results in

$$\dot{\mu}(t) = -e^{-rt}w + e^{-rt}ws(t) - e^{-rt}ws(t) + \mu(t)\delta, \quad \text{or,}$$

$$\dot{\mu}(t) = -e^{-rt}w + \mu(t)\delta. \tag{68}$$

Defining $p(t) = e^{rt}\mu(t)$ as the current (time t) value of an additional unit of human capital produced at time t, and taking the derivative of it with respect to time gives $\dot{p}(t) = re^{rt}\mu(t) + e^{rt}\dot{\mu}(t)$, or,

$$\dot{p}(t) = rp(t) + e^{rt}\dot{\mu}(t). \tag{69}$$

Substituting Equation (68) into Equation (69) delivers the final desired differential equation for the marginal benefit of accumulating one more unit of human capital at time t

$$\dot{p}(t) = p(t)\Big(r + \delta\Big) - w. \tag{70}$$

Marginal benefit of accumulating one more unit of human capital

$p(t)$, the current value of an additional unit of human capital produced at time t, is also equal to the discounted value of the additions to income (originated from the undepreciated amount of new human capital)

$$p(t) = w \int_t^T e^{-(r+\delta)\nu} d\nu = \frac{w}{r+\delta}\Big[1 - e^{-(r+\delta)(T-t)}\Big]. \tag{71}$$

Taking derivative of $p(t)$ with respect to time delivers

$$\dot{p}(t) = -we^{-(r+\delta)(T-t)}. \tag{72}$$

Substituting Equations (71) and (72) into the differential equation (70) verifies that $p(t)$ is the solution of the system and represents the marginal benefit of acquiring one more unit of human capital.

Also, the negative sign of $\dot{p}(t)$ in Equation (72) shows that the marginal benefit of accumulating human capital declines over the life cycle and it will be zero at $t = T$, as depicted by Equation (71).

Marginal cost of accumulating one more unit of human capital

Deriving the equation for the marginal cost of producing human capital requires taking the derivative of investment cost, $c(t)$, with respect to $q(t)$, the production flow of human capital. To do so, firstly, it is vital to express Equation (9) in terms of $q(t)$, the human capital produced shown in Equation (6) and the model parameters.

Dividing both sides of equations (65) and (67) delivers

$$p_d d(t) = \frac{\beta}{\alpha} ws(t)h(t), \tag{73}$$

$$d(t) = \frac{\beta}{\alpha p_d} ws(t)h(t). \tag{74}$$

Substituting Equation (73) into Equation (9) gives

$$c(t) = \frac{\alpha+\beta}{\beta} ws(t)h(t). \tag{75}$$

In Equation (75), I need to express $s(t)h(t)$ in terms of $q(t)$ and the model parameters.

In this regard, rewrite the Equation (6) as

$$d(t) = \Big(\frac{q(t)}{a\big(s(t)h(t)\big)^{\alpha}}\Big)^{1/\beta}, \tag{76}$$

and equate the two Equations (74) and (76) to find

$$s(t)h(t) = \Big(\frac{q(t)^{1/\beta}\alpha p_d}{a^{1/\beta}\beta w}\Big)^{\beta/(\alpha+\beta)}. \tag{77}$$

Substituting Equation (77) into Equation (75) delivers the final relationship of the human capital investment cost in terms of curvature parameters (α, β), ability (a), price of inputs (p_d), skill price (w), and the addition to the human capital, $q(t)$

$$c(t) = w\frac{\alpha+\beta}{\alpha}\Big(\frac{q(t)}{a}\Big)^{1/(\alpha+\beta)}\Big(\frac{\alpha p_d}{\beta w}\Big)^{\beta/(\alpha+\beta)}. \tag{78}$$

Differentiating equation (78) with respect to $q(t)$ delivers the marginal cost of investing in human capital

$$MC(t) = \frac{w}{a\alpha}\Big(\frac{\alpha p_d}{\beta w}\Big)^{\beta/(\alpha+\beta)}\Big(\frac{q(t)}{a}\Big)^{[1/(\alpha+\beta)]-1}. \tag{79}$$

Optimal production of human capital

Equating marginal benefit, $p(t)$, from Equation (71) and marginal cost, $MC(t)$, from Equation (79) delivers the optimal level of human capital produced at time t

$$q(t) = a\Big(\frac{a\alpha}{r+\delta}\Big)^{(\alpha+\beta)/(1-\alpha-\beta)}\Big(\frac{\beta w}{\alpha p_d}\Big)^{\beta/(1-\alpha-\beta)}\Big[1 - e^{-(r+\delta)(T-t)}\Big]^{(\alpha+\beta)/(1-\alpha-\beta)}. \tag{80}$$

Ben-Porath model in discrete-time

As shown in Equation (73), the direct cost of investment, $p_d d(t)$, is just a multiple of the time cost of investment in human capital, $ws(t)h(t)$. Therefore, assuming away $d(t)$ and analyzing the Ben-Porath model in discrete time is generally convenient. In this case, the maximization problem is solved by the Bellman equation and gives the choices of individuals for the time investment in human capital in each period.

B.3 Roy (1951)

The author explains the condition in which self-selection accrues. Following is an attempt to explain these conditions using mathematical notations. Income maximizing agents possess two skills, S_1 and S_2, representing the agents' output in fishing and hunting, the number of fish and rabbits. The income of a fisherman and a hunter is $Y_1 = \pi_1 S_1$ and $Y_2 = \pi_2 S_2$, where skill prices are π_1 and π_2, respectively.[2] Skills could also represent the stock of the human capital or earnings ability and follow a log-normal joint distribution

$$\begin{pmatrix} \ln S_1 \\ \ln S_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \right). \tag{81}$$

Define dispersion of skill (ability) as the difference between the logarithms of abilities and their population mean,

$$U_i = \ln S_i - \mu_i. \tag{82}$$

Using Equation (82), the following relationship holds

$$\ln Y_i = \ln \pi_i + \ln S_i = \ln \pi_i + \mu_i + U_i. \tag{83}$$

Using Equations (81) and (82), distribution of U_i could be written as

$$\begin{pmatrix} U_1 \\ U_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \right). \tag{84}$$

I focus on the fishing occupation (sector 1) in the following operations. Due to the symmetry, the hunting sector results would be similar to fishing results. The self-selection dictates the mean earnings of those observed as a fisherman, on average, is higher than that

[2] For income and outputs, I use upper-case letters for random variables and lower-case letters for their realizations.

of hunters if they choose to fish. In other words, the average of log-earnings conditional on being a fisherman is higher than the unconditional log-income mean of fishing for the whole population

$$\mathbb{E}(\ln Y_1 | \ln Y_1 > \ln Y_2) > \mathbb{E}(\ln Y_1). \tag{85}$$

Substituting Equation (83) in Equation 85 results in

$$\mathbb{E}\Big[(\ln \pi_1 + \mu_1 + U_1)|(\ln \pi_1 + \mu_1 + U_1) > (\ln \pi_2 + \mu_2 + U_2)\Big] > \mathbb{E}\Big[(\ln \pi_1 + \mu_1 + U_1)\Big]. \tag{86}$$

Defining $c_i = \ln \pi_i + \mu_i$ as a constant will result in

$$c_1\,\mathbb{E}\Big[U_1|(c_1 + U_1) > (c_2 + U_2)\Big] > c_1\,\mathbb{E}\,(U_1). \tag{87}$$

From Equation (84) $\mathbb{E}(U_1) = 0$, therefore

$$\mathbb{E}\Big[U_1|(U_1 - U_2) > (c_2 - c_2)\Big] > 0. \tag{88}$$

Since U_1 and $U_1 - U_2$ are dependent, I can write the following regression

$$U_1 = \alpha(U_1 - U_2) + \nu. \tag{89}$$

Substituting Equation (89) into Equation (88), gives

$$\mathbb{E}\Big[\alpha(U_1 - U_2) + \nu|(U_1 - U_2) > (c_2 - c_2)\Big] > 0. \tag{90}$$

Taking α out of the Expectation operator and multiplying and dividing both sides of Equation (90) by σ delivers

$$\alpha\sigma\,\mathbb{E}\Big[\frac{(U_1 - U_2)}{\sigma}|\frac{(U_1 - U_2)}{\sigma} > \frac{(c_2 - c_2)}{\sigma}\Big] > 0. \tag{91}$$

Based on the definition, the coefficient of the regression in Equation (89) is defined as

$$\alpha = \frac{Cov(U_1, U_1 - U_2)}{Var(U_1 - U_2)} = \frac{\sigma_{11} - \sigma_{12}}{\sigma^2}, \text{ where } \sigma^2 = \sigma_{11} + \sigma_{22} - 2\sigma_{12}. \tag{92}$$

Substituting Equation (92) into Equation (91) gives

$$\frac{\sigma_{11} - \sigma_{12}}{\sigma} \mathbb{E}\Big[\frac{(U_1 - U_2)}{\sigma} | \frac{(U_1 - U_2)}{\sigma} > \frac{(c_2 - c_2)}{\sigma}\Big] > 0. \tag{93}$$

Based on the definition of inverse Mills ratio, the following relationship holds

$$\mathbb{E}\Big[\frac{(U_1 - U_2)}{\sigma} | \frac{(U_1 - U_2)}{\sigma} > \frac{(c_2 - c_2)}{\sigma}\Big] = \lambda\Big[\frac{(c_2 - c_2)}{\sigma}\Big], \tag{94}$$

where $\lambda(.) = \phi(.)/(1 - \Phi(.))$, $\phi(.)$ and $\Phi(.)$ represent Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of a random variable, respectively. Therefore, Equation (93) could be written as

$$\frac{\sigma_{11} - \sigma_{12}}{\sigma} \overbrace{\left\{ \frac{(\frac{\phi(c_2 - c_1}{\sigma})}{(\frac{\Phi(c_2 - c_1}{\sigma})} \right\}}^{\text{positive}} > 0. \tag{95}$$

Since the sign of σ is positive, then the sign of the left-hand side of Equation (95) boils down to the sign of $\sigma_{11} - \sigma_{12}$, where σ_{11} is the variance or the dispersion of fishing skill and σ_{12} is the covariance between fishing and hunting skills.

B.4 Willis and Rosen (1979)

An individual's choice is restricted to two schooling-occupation categories by assuming a strong link between the schooling level and the occupational sector. The sectors are mutually exclusive and exhaustive.

College education prepares individuals for the category "A" type of occupations, and high school education makes individuals ready for the "B" type of occupational sector. It is assumed that individuals are certain about completing the years of attending college and choosing that level of schooling. The group "A" represents "college attendees", those who entered college but not all group members may complete college studies. Individuals' potential earnings are defined as

$$
\begin{array}{lll}
y_{ai}(t) = 0 & 0 \leq t < s \ , & \text{college attendee while in college,} \\
y_{ai}(t) = \bar{y}_{ai} \ \exp\Big(g_{ai}(t-s)\Big) & s \leq t < \infty \ , & \text{college attendee after college,} \\
y_{bi}(t) = \bar{y}_{bi} \ \exp(g_{bi}t) & 0 \leq t < \infty \ , & \text{high school graduate,}
\end{array}
$$

where $y_{ai}(t)$ and $y_{bi}(t)$ are potential earnings streams if individual i becomes a college graduate or a high school graduate, respectively. $\bar{y}_{ji}$, $j \in \{a, b\}$ are the initial wages, and g_{ji} are the growth rates of earnings for these two categories which shape the earnings prospects of each person in the population. s is the number of years in college with no direct schooling costs, and $(t-s)$ is the post-college possible work experience.

In an infinite horizon model, individuals maximize their present value of lifetime earnings and compare these present values in both potential occupations,

$$V_{ai} = \int_s^\infty \exp(-r_i t) \ y_{ai}(t)dt = \Big(\bar{y}_{ai}/(r_i - g_{ai})\Big) \exp(-r_i s), \quad \text{if college is chosen,} \tag{96}$$

$$V_{bi} = \int_0^\infty \exp(-r_i t) \ y_{bi}(t)dt = \ \bar{y}_{bi}/(r_i - g_{bi}), \quad \text{if college is not the choice,} \tag{97}$$

where r_i is the individual-specific subjective constant discount rate ($r_i > g_{ai}, g_{bi}$).

The authors allow for individual heterogeneity in college and high school earnings $(\bar{y}_{ai}, \bar{y}_{bi})$, college and high school earnings growth (g_{ai}, g_{bi}), and interest rates (r_i). They assume that $(\bar{y}_{ai}, \bar{y}_{bi}, g_{ai}, g_{bi}, r_i)$ are randomly distributed in the population.

The following operations represent the relevant steps to derive the present value of potential lifetime earnings for category A as a college attendee. The same procedure applies to category B as a high school graduate.

$$\begin{aligned}
V_{ai} &= \int_s^\infty \exp(-r_i t)\ y_{ai}(t)dt, \\
&= \int_s^\infty \exp(-r_i t)\ \bar{y}_{ai}\ \exp\Big(g_{ai}(t-s)\Big)dt, \\
&= \bar{y}_{ai}\ \int_s^\infty \exp\Big(g_{ai}(t-s) - r_i t\Big)dt, \\
&= \Big(\bar{y}_{ai}/(g_{ai}-r_i)\Big)\exp\Big(g_{ai}(t-s) - r_i t\Big)\Bigg|_s^\infty, \\
&= \Big(\bar{y}_{ai}/(g_{ai}-r_i)\Big)\exp\Big(\underbrace{(-r_i+g_{ai})}_{negative}t - g_{ai}s\Big)\Bigg|_s^\infty, \\
&= \Big(\bar{y}_{ai}/(g_{ai}-r_i)\Big)\Big(\exp(-\infty) - \exp(-r_i s)\Big), \\
&= \Big(\bar{y}_{ai}/(g_{ai}-r_i)\Big)\Big(-\exp(-r_i s)\Big), \\
&= (\bar{y}_{ai}/(r_i - g_{ai}))\exp(-r_i s).
\end{aligned}$$

As shown in Equations (98) to (102), these individual-specific items are characterized by individuals' observed characteristics and some unobserved components

$$\ln \bar{y}_{ai} = X_i\beta_a + u_{1i}, \quad \text{if college is chosen,} \tag{98}$$

$$g_{ai} = X_i\gamma_a + u_{2i}, \tag{99}$$

$$\ln \bar{y}_{bi} = X_i\beta_b + u_{3i}, \quad \text{if college is not chosen,} \tag{100}$$

$$g_{bi} = X_i\gamma_b + u_{4i}, \tag{101}$$

$$r_i = Z_i\eta + u_{5i}. \tag{102}$$

The essence of Willis and Rosen is about self-selection based on endowments (schooling abilities and financing constraints). X is the set of observed schooling ability variables.[3] $\{u_1, \ldots, u_4\}$ denote permanent individual-specific unobserved components reflecting unmeasured factors influencing earnings potential.

[3]The observed ability variables in X are mathematics, reading-comprehension test scores (the psychometric mental tests known as highly correlated with IQ score), manual dexterity, and mechanical ability test scores (the physical ability tests more associated with manual skills).

The authors assume that the individual discount rate (r_i) varies in line with a person's socioeconomic status represented by the family-background measures (Z) reflecting financial constraints, tastes, and perceptions.[4] u_5 is a permanent unobserved component influencing financial barriers to school choice. Vector $\boldsymbol{U} = \{u_1, \dots, u_5\}$ is assumed to be jointly normal, with mean $\mathbf{0}$ and unrestricted variance-covariance matrix, $\mathbf{\Sigma} = [\sigma_{ij}]$.

The main goal of the paper

The authors' main goal is to demonstrate the empirical relevance of comparative advantage and selectivity issues. In other words, whether the observed mean earnings (or the growth rate of wages) of individuals in a particular career j they have selected is higher than the potential mean earnings for all individuals in the population if all had chosen to work in the same profession

$$\mathbb{E}(\ln \bar{y}_j | \text{ alternative } j \text{ is chosen}) > \mathbb{E}(\ln \bar{y}_j),$$
$$\mathbb{E}(g_j | \text{ alternative } j \text{ is chosen}) > \mathbb{E}(g_j).$$

To do this experiment, the authors first define a college decision rule to create a choice probability model. Then, they create regression models conditional on college enrollment that correspond to potential outcomes of the model economy, Equations (98) to (101). Finally, they use the observed data to estimate the desired parameters and discuss the results to find the notions of the "selectivity bias": individuals self-select into occupations with comparative advantages.

Decision rule to enroll in college

The authors define a criterion for occupational choice based on the present value of lifetime earnings: individuals choose college if

$$V_{ai} > V_{bi}.$$

[4]The examples of variables in Z are parental education, father's occupation, mother's work activity, number of siblings, and so on.

Also, define an index $I_i = \ln V_{ai} - \ln V_{bi}$, that describes the log of the relative lifetime utility of choosing schooling in college over the high school

$$I_i = \ln \bar{y}_{ai} - \ln(r_i - g_{ai}) - r_i s - \ln \bar{y}_{bi} + \ln(r_i - g_{bi}). \tag{103}$$

Then take the Taylor series approximation to the nonlinear terms around their population mean values $(\bar{g}_a, \bar{g}_b, \bar{r})$),

$$\ln(r_i - g_{ai}) = \bar{r} - \bar{g}_a + \frac{1}{(\bar{r} - \bar{g}_a)}(r_i - \bar{r}) - \frac{1}{(\bar{r} - \bar{g}_a)}(g_{ai} - \bar{g}_a), \tag{104}$$

$$\ln(r_i - g_{bi}) = \bar{r} - \bar{g}_b + \frac{1}{(\bar{r} - \bar{g}_b)}(r_i - \bar{r}) - \frac{1}{(\bar{r} - \bar{g}_b)}(g_{bi} - \bar{g}_b). \tag{105}$$

Substitute equations (104) and (105) into equation (103) results in

$$I_i = \alpha_0 + \alpha_1(\ln \bar{y}_{ai} - \ln \bar{y}_{bi}) + \alpha_2 g_{ai} + \alpha_3 g_{bi} + \alpha_4 r_i, \tag{106}$$

where $\alpha_0 = \bar{g}_a - \bar{g}_b, \alpha_1 = 1, \alpha_2 = \frac{1}{\bar{r}-\bar{g}_a}, \alpha_3 = \frac{-1}{\bar{r}-\bar{g}_b}, \alpha_4 = -\left[s + \frac{\bar{g}_a - \bar{g}_b}{(\bar{r}-\bar{g}_a)(\bar{r}-\bar{g}_b)}\right] = -(s + \alpha_0\alpha_2\alpha_3)$.

Structural model is the set of equations (98) to (102), (106), and the following **choice probabilities** in terms of choice index

$$\Pr(\text{A is observed}) = \Pr(V_a > V_b) = \Pr(I > 0),$$
$$\Pr(\text{B is observed}) = \Pr(V_a \leq V_b) = \Pr(I \leq 0).$$

Determining selection bias by using observed earnings

The wages and their growth rate for both categories in the data are only observed for individuals who have already self-selected in that category (factual sample data), either as high school or college enrollees. These wages might be different than the population's if all had selected the same type of education. Therefore, to determine the presence of positive selectivity and the notion of comparative advantage, the authors model the conditional expectations of initial wages and growth rates of earnings conditioned on self-selection into the relevant categories. To estimate the parameters related to the "selectivity bias," the authors' empirical approach consists of a two-stage method: the first stage is a reduced form probit for college attendance, and the second step is a series of wage regressions, including inverse Mills ratios. The following briefly describes these two steps.

Step 1 - Estimate the reduced-form probit model to obtain estimations for the inverse Mills ratios

This step first requires representing the structural model by a reduced-form equation and then estimating the inverse of Mill's ratio (based on the two-stage procedure of Heckman, 1979). substituting equations (98) to (102) into equation (106) delivers a reduced-form equation for the selection rule as

$$\begin{aligned} I_i = \overbrace{\alpha_0}^{\pi_0} + X \overbrace{\left[\alpha_1(\beta_a - \beta_b) + \alpha_2\gamma_a + \alpha_3\gamma_b\right]}^{\pi_1} + Z \overbrace{\left[\alpha_4\eta\right]}^{\pi_2} + \\ \underbrace{\left[\alpha_1(u_1 - u_3) + \alpha_2 u_2 + \alpha_3 u_3 + \alpha_5 u_5\right]}_{-\varepsilon}. \end{aligned} \tag{107}$$

Equation (107) could be represented by

$$I_i = W_i\pi - \varepsilon_i \quad \text{where } W_i = [X_i, Z_i]. \tag{108}$$

The above equation implies that

$$\Pr(A \text{ is chosen}|W_i) = \Pr(I_i > 0) = \Pr(\varepsilon_i < W_i\pi) = F\left(\frac{W_i\pi}{\sigma_\varepsilon}\right). \tag{109}$$

Equation (109) is a probit function determining sample selection into college attendance (option A) and high school only (option B). $W_i\pi/\sigma_\varepsilon$ is the standardized truncation point and $F()$ is the standard normal CDF. $\widehat{\pi/\sigma_\varepsilon}$ could be found by estimating the above reduced-form probit model. Using $\widehat{\pi/\sigma_\varepsilon}$, the estimates for the inverse Mills ratios could be found

$$\widehat{\lambda_a}(W\widehat{\pi/\sigma_\varepsilon}) \equiv -\Big[f(W\widehat{\pi/\sigma_\varepsilon})/F(W\widehat{\pi/\sigma_\varepsilon})\Big] < 0,$$
$$\widehat{\lambda_b}(W\widehat{\pi/\sigma_\varepsilon}) \equiv (f(W\widehat{\pi/\sigma_\varepsilon})/\Big[1 - F(W\widehat{\pi/\sigma_\varepsilon})\Big] > 0.$$

These estimates, $\widehat{\lambda_a}(.)$ and $\widehat{\lambda_b}(.)$, are defined as the ratio of the standard normal PDF and CDF of estimated truncation points $(W\widehat{\pi/\sigma_\varepsilon})$ and will be used as explanatory variables in the regression models presented in the following step.

Step 2 - Estimating equations of the expected earnings and growth rates in terms of observed data and inverse Mills ratios

The wages and their growth rate for both categories in the data are only observed for individuals who have already self-selected in that category (factual observed data). These wages might differ from the population's if all had selected the same category.

Therefore, the authors derive the following conditional expectation equations to determine the presence of positive selectivity and the notion of comparative advantage. Equations (110) to (113) show the individuals' expected outcomes conditional on their occupational choices, either the initial wages and growth rates of earnings for individuals who have chosen to pursue college studies $(I > 0)$ or those of individuals who have not chosen higher studies $(I \leq 0)$

$$\mathbb{E}(\ln \bar{y}_a | I > 0) = X\beta_a + \frac{\sigma_{1\varepsilon}}{\sigma_\varepsilon}\lambda_a(W\pi/\sigma_\varepsilon), \tag{110}$$

$$\mathbb{E}(g_a | I > 0) = X\gamma_a + \frac{\sigma_{2\varepsilon}}{\sigma_\varepsilon}\lambda_a(W\pi/\sigma_\varepsilon), \tag{111}$$

$$\mathbb{E}(\ln \bar{y}_b | I \leq 0) = X\beta_b + \frac{\sigma_{3\varepsilon}}{\sigma_\varepsilon}\lambda_b(W\pi/\sigma_\varepsilon), \tag{112}$$

$$\mathbb{E}(g_a | I \leq 0) = X\gamma_b + \frac{\sigma_{4\varepsilon}}{\sigma_\varepsilon}\lambda_b(W\pi/\sigma_\varepsilon). \tag{113}$$

where $\sigma_{k\varepsilon} = cov(u_k, \varepsilon),\ k = 1 \ldots 4$. In the above equations, the authors used the truncated joint normal distribution of error terms in Equations (98) to (101) and Equation (108) truncated at ($\varepsilon < W\pi$) equivalent to ($I > 0$) for individuals who attended college.[5]

Consider the following regression equations. Using data on initial earnings and their growth rates, the following equations could be estimated

$$\ln \bar{y}_a = X\beta_a + \beta_a^* \widehat{\lambda_a}(\widehat{W\pi/\sigma_\varepsilon}) + \nu_1, \tag{114}$$

$$g_a = X\gamma_a + \gamma_a^* \widehat{\lambda_a}(\widehat{W\pi/\sigma_\varepsilon}) + \nu_2, \tag{115}$$

$$\ln \bar{y}_b = X\beta_b + \beta_b^* \widehat{\lambda_b}(\widehat{W\pi/\sigma_\varepsilon}) + \nu_3, \tag{116}$$

$$g_b = X\gamma_b + \underbrace{\gamma_b^* \widehat{\lambda_b}(\widehat{W\pi/\sigma_\varepsilon})}_{\substack{\text{selectivity correction} \\ \text{terms}}} + \nu_4. \tag{117}$$

Equations (114) to (117) are called "selectivity-bias-corrected" structural equations for individuals conditional on their occupational choices.

These equations have an additional term on the right-hand side compared to the population's initial wages and growth rates of earnings of all individuals, (98) to (101). These additional terms on the right-hand side are named "selectivity correction terms." These equations show a positive selectivity bias if the second terms are positive. It means that the average initial earnings or the growth rate for that specific individual sample are higher than that of the whole population had they chosen to self-select in that particular group.

In this regard, it is required to estimate $\widehat{\beta_a^*}$, $\widehat{\gamma_a^*}$, $\widehat{\beta_b^*}$, and $\widehat{\gamma_b^*}$. They represent the estimations for $\sigma_{1\varepsilon}/\sigma_\varepsilon$, $\sigma_{2\varepsilon}/\sigma_\varepsilon$, $\sigma_{3\varepsilon}/\sigma_\varepsilon$, and $\sigma_{4\varepsilon}/\sigma_\varepsilon$ in Equations (110) to (113). The estimated values of

[5] To derive the conditional expectation equations, the authors follow the following steps. As an example, for those selected to enroll in college, the conditional mean of wages is derived from Equation (98)

$$\begin{aligned}
\ln \bar{y}_{ai} &= X_i\beta_a + u_{1i}, \\
E(\ln \bar{y}_a | I > 0) &= X\beta_a + \mathbb{E}(u_1 | I > 0), \\
&= X\beta_a + \mathbb{E}(u_1 | \varepsilon < W\pi), \\
&= X\beta_a + \frac{cov(u_1, \varepsilon)}{var(\varepsilon)} \mathbb{E}(\varepsilon | \varepsilon < W\pi), \\
&= X\beta_a + \frac{\sigma_{1\varepsilon}}{\sigma_\varepsilon^2} \sigma_\varepsilon \mathbb{E}\left(\frac{\varepsilon}{\sigma_\varepsilon} | \frac{\varepsilon}{\sigma_\varepsilon} < \frac{W\pi}{\sigma_\varepsilon}\right), \\
&= X\beta_a + \frac{\sigma_{1\varepsilon}}{\sigma_\varepsilon} \lambda_a(W\pi/\sigma_\varepsilon).
\end{aligned}$$

these coefficients will reveal the sign of the "selectivity correction terms" and the presence of the selectivity bias for initial earnings and rates of growth for both educational categories. Since $\widehat{\lambda_a}$ ($\widehat{\lambda_b}$) is negative(positive), the selectivity bias will be positive if $\beta_a^* < 0$, $\gamma_a^* < 0$, $\beta_b^* > 0$, $\gamma_b^* > 0$, representing the existence of comparative advantage in the schooling investment process.

The authors estimate the model on a sample of 3,611 respondents to the NBER-Thorndike-Hagen survey of 1968-71 comprised of male WWII veterans who applied for the Army Air Corps and were eligible for the GI Bill. The dataset contains extensive information on family background and ability. All members of the dataset are at least high school graduates and more than 75% attended some college, partly attributable to the GI bill.

The disadvantage of this dataset is that it does not come from a random population sample, and the model results could not be generalized to the population at large. However, many advantages of the dataset make it very appealing. First, it covers more than 20 years of labour-market experience, which is most appropriate for measuring the lifetime earnings effects of educational choice. Second, it contains extensive information on ability indicators and family background, making the dataset suitable for testing comparative advantage theory.

B.5 Keane and Wolpin (1997)

KW(97)'s model is categorized as a Discrete Choice Dynamic Programming (DCDP) model. Therefore, first, I explain DCDP models. This type of model is widely used in economics to model forward-looking discrete decisions and has become a hallmark of empirical microeconomics. DCDP models explain decision-maker choices among various alternatives. The decision-makers can be individuals, households, firms, etc., who maximize expected inter-temporal payoffs. The alternatives may represent competing products, courses of action, or other options. The structural parameters of the model are estimated using micro-data on decision-maker choices and payoffs.[6]

Accounting for unobserved heterogeneity, therefore, dynamic selection is essential to many economic problems and is a standard feature of dynamic discrete choice models in labour economics. A vast empirical literature uses DCDP modes with applications in labour economics, industrial organization, economic demography, health economics, development economics, political economy, and marketing.

The DCDP literature can be broadly categorized into partial and general equilibrium models. Some example of papers using DCDP models amongst many others are: Job search (Wolpin, 1987), optimal timing of machine replacement (Rust, 1987), educational and career choice (Arcidiacono, 2004; Keane & Wolpin, 1997; Sullivan, 2010), high school dropout behaviour (Eckstein & Wolpin, 1999), the relationship between earnings dispersion (wage and employment rate volatility) and education (Belzil & Hansen, 2004), labour supply of married women (Eckstein & Lifshitz, 2015; Eckstein & Wolpin, 1989a; Francesconi, 2002), congressional careers (Diermeier, Keane, & Merlo, 2005), effect of subsidies on children school attendance (Wolpin & Todd, 2006), dynamic brand choice (Crawford & Shum, 2005), dynamic pricing decisions (Ching, 2010), career cost of children (Adda, Dustmann, & Stevens, 2017), child care policies (Chan & Liu, 2018), political corruption (Finan & Mazzocco, 2021), illegal drugs and educational attainment (Mezza & Buchinsky, 2021).[7]

General setup of Discrete Choice Dynamic Programming (DCDP) models

All Discrete Choice Dynamic Programming models, even the most complicated and recent ones, could be written by the following general framework. Consider a set of alternatives, $\boldsymbol{M}$, called the *"choice set"*. This set of alternatives needs to have two main characteristics: *mutually exclusive*, and *finite number of alternatives*. Mutually exclusive alternatives mean the decision-maker chooses only one alternative from the choice set. The appropriate

[6]Parameters are called *structural* because they characterize agents' preferences and beliefs about technological and institutional constraints (Aguirregabiria & Mira, 2010).

[7]For surveys describing the methodology and providing examples of applications, see Arcidiacono and Miller (2020), Levy and Schiraldi (2020), Blundell (2017), Low and Costas (2017), Arcidiacono and Ellickson (2011), Keane, Todd, and Wolpin (2011), Aguirregabiria and Mira (2010), Keane and Wolpin (2009), Belzil (2007), Wolpin (2003), Miller (1997), Rust (1996), Rust (1994), Eckstein and Wolpin (1989b).

specification of the choice set largely depends on the research goals and the data available to the researchers. For example, a choice set could consist of four alternatives: studying at school, staying at home, working in a white-collar occupation, or a blue-collar occupation. The choice set has a finite number of alternatives, and individuals choose one and only one alternative in each period over T discrete periods. Then, the associated choice variable is defined as

$$d_m(t) = \begin{cases} 1 & \text{if } m \text{ is chosen,} \\ 0 & \text{otherwise.} \end{cases}$$

The random reward function $R_m(t; \boldsymbol{X}, \boldsymbol{\varepsilon}, \boldsymbol{\theta})$ is associated with each choice m, where $\boldsymbol{\theta}$ is a vector of parameters. The randomness of the reward function comes from the stochastic state variable, $\boldsymbol{\varepsilon}$. $\boldsymbol{X}$ is a vector of individual characteristics or observed state variables. $\boldsymbol{X}$ can contain many variables. The current choices do not directly influence them. However, they may be affected by choices made in previous periods. In dynamic models, the past choices affect the current states and, thus, the current choice, whereas, in static models, the past choices do not influence current states (Keane & Wolpin, 2009). The following shows the inter-temporal feature of Discrete Choice Dynamic Programming models

$$\boldsymbol{X}(t) \Longrightarrow d_m(t) \Longrightarrow \boldsymbol{X}(t+1) \Longrightarrow d_m(t+1) \Longrightarrow \ldots \Longrightarrow d_m(T-1) \Longrightarrow \boldsymbol{X}(T) \Longrightarrow d_m(T).$$

DCDP models are usually derived under an assumption of the utility-maximizing behaviour of the decision-maker. The utility depends on unknown parameters to the researcher and therefore needs to be estimated statistically. The objective of the individual at any time t is to maximize

$$\mathbb{E}\left\{ \sum_{\tau=t}^{T} \beta^{\tau-t} \sum_{m\in M} R_m(\tau; \boldsymbol{X}, \boldsymbol{\varepsilon}, \boldsymbol{\theta}) d_m(\tau) \middle| \boldsymbol{S}(t) \right\},$$

where $0 < \beta < 1$ is the rate at which the agent discounts utility in future periods.[8] T is either finite or infinite ($T < \infty$ or $T = \infty$).[9] $\mathbb{E}(.)$ is the mathematical expectation operator, and $\boldsymbol{S}(t)$ is the individual's information set or state-space at time t. The state space contains

[8] The discount rate could be fixed or could be estimated along with the other parameters $\{\beta, \theta\}$.

[9] Most applications of DCDP models assume that agents solve a finite horizon problem in discrete time.

all factors known to the individual that affect current rewards or the probability distribution of future rewards.

In the DCDP model, either all individuals start from the same state variables, $\boldsymbol{X}$, (Keane & Wolpin, 1994, as an example), or agents are grouped into a finite number of "types" with identical inter-group initial characteristics (see, for example Keane & Wolpin, 1997). What makes individuals different in the following periods is a stochastic term, ε_t, introduced into their reward function (*e.g.* wage equation).

At each period, there are mutually exclusive choices, $\{d_m(t)\}_{m\in\boldsymbol{M}}$, and the individual chooses just one choice out of all available choices.[10] Therefore, depending on a specific choice outcome, at each time, t, there would be just one actual realized reward defined as

$$R(t) = \sum_{m\in M} \underbrace{R_m(t;\boldsymbol{X},\boldsymbol{\varepsilon},\boldsymbol{\theta})}_{\substack{\text{per period}\\ \text{reward from}\\ \text{choice } m}} \underbrace{d_m(t)}_{\substack{\text{choice}\\ \text{indicator}}} .$$

Suppose one ignores ε_t and assumes that the reward function is deterministic; then, by starting from the same state variables, $\boldsymbol{X}$, all individuals have the same reward functions and will make the same decisions. This result is odd with the observed behaviour of individuals in the data. Therefore, the model allows for the heterogeneity in the reward function by using the stochastic term, ε_t, either as an additive or multiplicative term. The assumption is that individuals draw ε_t at each time t from a density function. At each period, ε_t is known to the individual but not known to the observing economist. This feature makes the observed decision random from the economists' perspective.

Maximization of the objective function is achieved by choice of the optimal sequence of control variables $\{d_m(t)\}_{m\in\boldsymbol{M}}$ for $t = 0,\ldots,T$. Therefore, one can define the maximal expected value of the discounted lifetime reward at time t as

$$V(S(t),t) = \max_{\{d_m(t)\}_{m\in\boldsymbol{M}}} \mathbb{E}\left\{ \sum_{\tau=t}^{T} \beta^{\tau-t} R(\tau) \middle| \boldsymbol{S}(t) \right\}.$$

[10] $\sum\{d_m(t)\}_{m\in\boldsymbol{M}} = 1$ where $t = 0,\ldots,T$.

The researcher collects data on individuals' choices and the relevant rewards they gain based on their choices over time. The goal is to fit the model to the observed data and estimate the model's parameters, $\boldsymbol{\theta}$.

Estimation procedures

The dataset is a panel of N individual, $n = 1.\dots, N$. The researcher follows these individuals over periods, $t = 0, \dots, T$. Then for each time, an individual decides over M discrete choices, $m = 1, \dots, M$. The researcher observes the choices of the individuals, $d_m^n(t)$, as binary variables and other individuals' characteristic variables, $\boldsymbol{X}^n(t)$, as regressors. Also, the researcher may observe reward functions such as wages. The implementation of a Dynamic Discrete Choice Model needs two fundamental steps.

First, the dynamic problem could be solved using a given initial set of parameters. The second step is estimating the parameters of the model. The estimation process involves an iterative optimization procedure over the relevant parameter space to maximize an objective function (or minimize a distance). Estimation could be done by various techniques such as Maximum Likelihood Estimation (MLE) or simulation-based estimation methods such as Maximum Simulated Likelihood Estimation (MSLE) and Method of Simulated Moments (MSM).

Maximum likelihood Estimation is implemented by constructing the likelihood function and then maximizing it for the parameters of interest. Usually, the logarithm of the likelihood function (i.e. the log-likelihood) is maximized, as it is numerically more convenient. In the case of discrete variables, as in DCDP, the likelihood function is the joint probability of the observed data.

Dynamic Roy model - Keane and Wolpin (1997)

The partial-equilibrium model of KW(97) allows individuals to make repeated choices over time, starting at age 16 and ending at age 65. Authors consider the maximization problem from age 16 as the last age of mandatory enrollment at high school (compulsory minimum level of schooling). Agents choose among five mutually exclusive and exhaustive alternatives ($M = 5$): 1- work in a blue-collar occupation, 2- work in a white-collar job, 3- work in the military, 4- attend school, or 5- engage in home production. At age 16, each individual has a fixed initial vector of skill endowments for all future activities

$$\boldsymbol{e}(16) = \{e_1(16), e_2(16), e_3(16), e_4(16), e_5(16)\}.$$

The vector of initial endowment, $\boldsymbol{e}(16)$, is attributed to various concepts such as learning ability, initial human capital, motivation, taste and the like. These endowments are unobservable to the researcher but observable to the individual. Individuals differ in their initial skill endowments, indicating unobserved skill heterogeneity in the model.

$e_1(16)$-$e_3(16)$ are the unobserved number of skill units in blue-, white-collar, and military occupations, respectively. These skill units in occupation equations mainly refer to the stock level of human capital, which could also be named as *earning ability*. $e_4(16)$ represents *learning ability* such as the level of initial cognitive ability or taste and motivation for schooling. $e_5(16)$ could be inferred as productivity in home production activity, or it may represent the taste or leisure value of staying home and doing nothing.

For the first three occupations, $m = 1, 2, 3$, at any age $a = 16, \ldots 65$, the reward functions (contemporaneous utilities), $R_m(a)$, are in terms of offered wages, $y_m(a)$,

$$R_m(a) = y_m(a) = w_m(a)e_m(a), \quad m = 1, 2, 3, \tag{118}$$

where $R_m(a)$ are the utility values of m^{th} alternative at age a, $w_m(a)$ is the occupation-specific skill rental price attached to the human capital used in occupation m.[11] At any age, the occupation-specific skills, $e_m(a)$, are accumulated based on the following human capital functions

$$e_m(a) = \exp\left[e_m(16) + \beta_{1m}s(a) + \beta_{2m}x_m(a) - \beta_{3m}x_m^2(a) + \epsilon_m(a)\right], \quad m = 1, 2, 3, \tag{119}$$

[11] wage and earnings could be interchangeably used because if agents are in the labour market, then they fully allocate their time to work.

where $s(a)$ is the schooling attainment at age a and β_{1m} is the return to schooling when working in sector m.[12] $x_m(a)$ is the work experience in occupation m at age a. β_{2m} and β_{3m} are the return to experience and square of experience in sector m, respectively. Both experience and schooling have deterministic law of motion, conditional on choices

$$s(a) = s(a-1) + d_4(a-1), \qquad 6 < s(a) < 21,$$

$$x_m(a) = x_m(a-1) + d_m(a-1), \quad m = 1, 2, 3,$$

where d_m equals one if alternative m is chosen at age a, zero otherwise. The transitory shocks, $\{\epsilon_m(a), m = 1, 2, 3\}$, appear in human capital functions as non-additive shocks. In other words, they are not additively separable. Skill production functions shown by Equation (119) are modified from the single-skill model (as in Ben-Porath, 1967) to a multi-skill production function to account for their occupation-specific nature. They also show that working experience has an investment value since it increases occupation-specific skills and, consequently, future earnings. This feature represents learning by doing (LBD) notion, which is absent in the Ben-Porath model. Substituting Equation (119) into (118) results in

$$y_m(a) = w_m(a) \exp\left[e_m(16) + \beta_{1m}s(a) + \beta_{2m}x_m(a) - \beta_{3m}x_m^2(a) + \epsilon_m(a)\right], \quad m = 1, 2, 3. \tag{120}$$

The standard practice is to estimate wages in logs, implying that these shocks appear as additive errors in the log wage equation, as expected. The wage equations have the Mincer form of being linear in years of education and quadratic in experience but with three different sets of returns to education and experiences for three distinct occupations

$$\ln y_m(a) = \underbrace{e_m(16)}_{\beta_{0m}} + \beta_{1m}s(a) + \beta_{2m}x_m(a) - \beta_{3m}x_m^2(a) + \epsilon_m(a), \quad m = 1, 2, 3,$$

where the skill prices, $w_m(a)$, are assumed to be constant over time and equally normalized

[12] $s(a)$ and $x_m(a)$ are inputs coming from data and β_{1m} to β_{3m} are coefficients to be estimated.

to one. The per-period reward for an individual who goes to school is

$$R_4(a) = e_4(16) - tc_1 \underbrace{\mathbb{1}\Big(s(a) \geq 12\Big)}_{\text{attend college}} - tc_2 \underbrace{\mathbb{1}\Big(s(a) \geq 16\Big)}_{\substack{\text{attend graduate} \\ \text{school}}} + \epsilon_4(a),$$

where tc_1 is the direct schooling costs (tuition costs) of college, and tc_2 is the additional net tuition costs for graduate school. $\mathbb{1}(.)$ is the indicator function set equal to one if the expression in the parentheses is a true statement, zero otherwise. $e_4(16)$ is endowed ability/taste for schooling at age 16, and $\epsilon_4(a)$ is a random shock to the monetary values of a year at school. The payoff to the school option, $R_4(a)$, is the consumption value (monetized value) of the utility/disutility of attending school, net of tuition costs. The home production sector has the following reward

$$R_5(a) = e_5(a) + \epsilon_5(a),$$

where $e_5(a)$ is the taste for staying at home at age 16 and $\epsilon_5(a)$ is a random shock to the monetary values at home.[13] The reward of the home option is the monetized value of leisure or home production. The vector of transitory shocks is choice-specific shocks to skill levels and the monetary values of a year at school or home, $\boldsymbol{\epsilon}(a) = \Big\{\epsilon_1(a), \epsilon_2(a), \epsilon_3(a), \epsilon_4(a), \epsilon_5(a)\Big\}$. These shocks fluctuate with age and are assumed to be joint normal, $\mathcal{N}(\mathbf{0}, \Omega)$, and serially uncorrelated. They are revealed in each period before individuals decide among the five options.

Agents maximize the expected present value of lifetime earnings plus the monetized value of non-pecuniary rewards over a finite horizon, starting from age 16 and ending at terminal age A=65. At any age, the individual's objective is to maximize the expected present value of remaining lifetime rewards at age a given the state space $\boldsymbol{S}(a)$ and discount factor β

$$V\Big(\boldsymbol{S}(a), a\Big) = \max_{m \in M} \Big\{V_m\Big(\boldsymbol{S}(a), a\Big)\Big\} = \max_{\{d_m(a)\}_{m \in M}} \mathbb{E}\left\{\sum_{\tau=a}^{A} \beta^{\tau-a} \sum_{m=1}^{5} R_m(\tau) d_m(\tau) \Big| \boldsymbol{S}(a)\right\}. \quad (121)$$

[13]"Taste" for schooling and "taste" for home are isomorphic with productivities in schooling and home sectors, respectively.

$\boldsymbol{S}(a) = \Big\{\boldsymbol{e}(16), s(a), \boldsymbol{x}(a), \boldsymbol{\epsilon}(a)\Big\}$ consists state variables observed by the agent at age a, where $\boldsymbol{x}(a)$ is the vector of work experiences in the three occupations: blue-collar, white-collar, and military jobs, i.e., $\boldsymbol{x}(a) = \Big\{x_1(a), x_2(a), x_3(a)\Big\}$. $d_m(a) = 1$ if alternative m is chosen at age a and zero otherwise. Equation (121) states that at any age a, agent calculates the choice-specific value functions, $V_m(\boldsymbol{S}(a), a)$, for all choices m, then chooses alternative m that maximizes V_m. The relevant Bellman equations for the alternative-specific value functions are

$$V_m(\boldsymbol{S}(a), a) = R_m(\boldsymbol{S}(a), a) + \beta\, \overbrace{\mathbb{E}\Big[V_m(\boldsymbol{S}(a+1), a+1) | \boldsymbol{S}(a),\ d_m(a) = 1\Big]}^{Emax\left(\boldsymbol{S}(a+1)\right)}, \quad a < A, \quad (122)$$

$$V_m(\boldsymbol{S}(A), A) = R_m(\boldsymbol{S}(A), A), \qquad a = A. \quad (123)$$

In the last period, A, the problem will be a static multinomial choice problem (using multinomial probit). The numerical solution method is done backward, starting from the last age in the model, A.

Estimation

To estimate the "basic" model, the authors add extra terms to the white- and blue-collar wage functions. They allow the white- (blue-) collar experience enters the blue- (white-) collar wage function and the military experience to enter both wage functions.[14]

The estimation procedure is similar to that of KW(94). However, there is an essential difference between the two models. In KW(94), all agents have the same initial predetermined (deterministic) state values (endowments) enter into the model at age 16, that is, $\bar{\boldsymbol{S}}(16) = \Big(s(16), x_1(16), x_2(16), d_3(15)\Big) = (10, 0, 0, 1)$.[15] However,

[14] Even by introducing partial transferable cross-experience terms in the white- and blue-collar wage equations, individuals, still accumulate occupation-specific human capital ($e_m(a), m = 1, 2$) through learning-by-doing mainly when engaged in their productive occupation (by working in the occupation m, where they use their comparative advantage). In real life, the experience accumulated in another job does not help much to get paid in the current job. In other words, individuals sell their comparative advantage, the skill and experience relevant to the current job, and the employer to have the job related to their experiences.

[15] All agents enter into the model at age 16 by ten years of schooling, $s(16) = 10$ (no discontinuation in education), zero job experience accumulated in either occupation, $x_1(16) = x_2(16) = 0$, and attended school in the previous year, $d_3(15) = 1$.

in KW(97), individuals' endowments at age 16 are not identical, that is, $\bar{\boldsymbol{S}}16) = \Big(s(16), x_1(16), x_2(16), x_3(16), e_1(16), e_2(16), e_3(16), e_4(16), e_5(16)\Big)$.

In KW(97), the initial conditions state that the level of schooling age 16, $s(16)$, is different among students. More importantly, agents' initial skill set, $\boldsymbol{e}(16)$, contains various combinations of different skills. Some have a higher stock of initial blue-collar occupation-specific skill, $e_1(16)$, and others may have a higher level of taste for staying at home and doing nothing, $e_5(16)$, among all other skills and preferences in their initial skill set. In other words, agents of the model have a comparative advantage over specific occupations or sectors, and therefore, they could be categorized into different "types" of individuals.

Therefore, KW(97) introduce a permanent unobserved heterogeneity (of individuals) in the form of "types" to the model. The authors assume that population distribution is approximated by a discrete distribution with four types of individuals. Each individual is characterized by a single time-invariant "type" $k \in \{1, \dots, 4\}$, observed by the individual at age 16.[16] Type k individual has an endowment vector, $\boldsymbol{e}_k(16)$, that depends on their innate abilities and prior human capital accumulation, denoted by

$$\boldsymbol{e}_k(16) = \{\boldsymbol{e}_{mk}(16) : m = 1, \dots, 5\}$$

Each individual has multinomial probability, $\pi_{k|s_n(16)}$, of belonging to each of these types, $k = 1, \dots, 4$. This multinomial probability, or the probability mass of each "type", must be identified and estimated by a fully structural approach. These probabilities are conditioned on observed differences in schooling attainment of individuals, $s_n(16)$, because model choices start from age 16 onward.[17]

Estimation and the post-estimation (simulation) results reveal that "type one" individuals are estimated to have a high cognitive skill of schooling and an increased endowment of white-collar skills. They are the "academic type" students who mainly complete college and work

[16]The type of the individual is assumed to be known to individuals but unknown to the researcher.

[17]Mixture models are commonly employed as a modelling device to account for unobserved heterogeneity. Cameron and Heckman (1998), Eckstein and Wolpin (1999), and Arcidiacono (2004, 2005) are other examples of using mixtures to control for person-specific differences in models of dynamic discrete choice.

in white-collar occupations. Also, they spend more years in school compared to other types. The "type two" students have high endowments of blue-collar skills, higher than all different types, and tend to move into blue-collar jobs after high school. Both "type three" and "type four" students have very low skill endowments. "Type four" individuals also have lower skill endowments but higher leisure values than "type three" and choose the home sector the most. Basically, "type three" people are the only ones to enter military jobs because they have a very low amount of skill endowments to work in white-collar occupations and have the most inferior taste for leisure. They generally move into the military or blue-collar work shortly after leaving high school.[18]

B.6 Altonji (1993)

Timing of the model

The two periods, $t = 1, 2$, represent the first and the second (final) college years, respectively. The model uses $t = 0$ to identify the pre-college or high school period. Before the college program starts, individuals must choose between going to work and attending the first year of college in either math/science, ST, or humanities/social sciences, AT.[19] At the end of time 0, individuals' endowments are the initial stock of human capital in two fields of study, $\boldsymbol{h}_0 = \{h_{0,ST}, h_{0,AT}\}$, and major-specific abilities, $\boldsymbol{a} = \{a_{ST}, a_{AT}\}$, representing math and verbal aptitudes, respectively. At the end of the first year in college, students may change their major or drop out and join the labour market.[20]

Human capital accumulation

During college periods, the accumulated level of knowledge at the end of the year, $\boldsymbol{h}_t = \{h_{t,ST}, h_{t,AT}\}$, depends on the stock of knowledge at the start of the year t, $\boldsymbol{h}_{t-1} =$

[18] Inferred from Table 11, p.507 and Table B1, p.518

[19] ST and AT denote STEM and ARTS, respectively. I replaced them for m and h in the original paper. The author also uses k for *knowledge or human capital*, which is usually represented by h in other literature. Therefore, I have modified these notations for more clarity and consistency in this dissertation.

[20] Similar to much of the learning literature, Altonji (1993) assumes that the labour market is an absorbing state, implying that leaving college is irreversible.

$\{h_{t-1,ST}, h_{t-1,AT}\}$, ability, $\boldsymbol{a} = \{a_{ST}, a_{AT}\}$, and a stochastic component.[21] A particular example of such a function, when major j is chosen, can be represented as

$$\boldsymbol{h}_t = \boldsymbol{\Pi}_{t,j}\boldsymbol{h}_{t-1} + \boldsymbol{\Phi}_{t,j}\boldsymbol{a} + \boldsymbol{\varepsilon}_t. \tag{124}$$

As Equation (124) shows, the accumulated level of knowledge at the end of the year t also depends on the field chosen, $j \in \{ST, AT\}$. The college courses are major-specific, and the field of study influences the mix of ST and AT courses taken in each major. These effects are captured by matrices $\boldsymbol{\Pi}_{t,j}$ and $\boldsymbol{\Phi}_{t,j}$ which put more weights on the major-specific components of human capital stock, $\boldsymbol{h}$, and ability, $\boldsymbol{a}$, relevant to the field of study, j, and the year, t. In other words, the human capital functions are field- and year-specific. Also, the error vector, $\boldsymbol{\varepsilon}_t$, captures the influence of particular teachers, courses and unforeseen individual-specific shocks (such as illness, emotional problems) that affect how much the student learns in the year t.

Degree requirements

A college degree in the field ST or AT requires that a field-specific level of knowledge, $h_{2,ST}$ or $h_{2,AT}$, exceed a threshold degree requirement. The probability that a person who is studying in field j in the second year will complete the degree requirements depending on the first year's endowments of ability and human capital

$$g_{2,j} = G_{2,j}(h_{1,ST}, h_{1,AT}, a_{ST}, a_{AT}) \text{ for } j \in \{ST, AT\}, \tag{125}$$

where both functions are strictly increasing in all arguments. The author assumes that the programs and the requirements for the two fields of study are sufficiently different that students who choose to study in the field $ST(AT)$ in the second period have a negligible chance of completing the degree requirements in $AT(ST)$.

In the first two periods ($t = 0, 1$), students do not know the exact probabilities of graduating from college in each field of study because the links between $\boldsymbol{h}_0$, $\boldsymbol{h}_1$, and $\boldsymbol{h}_2$

[21] The specific example of the human capital accumulation function is taken from Altonji (1991).

are stochastic, as shown in Equation (124). However, individuals know the probability distributions of completing the degree requirements in both fields, $g_{2,ST}$ or $g_{2,AT}$, at the end of the second year, conditional on attending college.

Earnings

Students who enter the labour market after high school receive y_0, their discounted present value of earnings at the time of decision-making at the end of period zero. Students who leave school after one year of college will receive $y_0(1+r_1)$, where r_1 is an earning parameter for dropout students. Therefore, the discounted present value of earnings for these students is defined as

$$y_1 = y_0(1+r_1)/(1+R),$$

where R is the discount rate. Similarly, those who attend college for a second year but fail to get a degree will receive $y_0(1+r_1)$. Consequently, their discounted present value of earnings is $y_0(1+r_1)/(1+R)^2$. But, for students who obtained a degree in the field ST and AT, will receive $y_0(1+r_{2,ST})$ and $y_0(1+r_{2,AT})$, respectively, where $r_{2,ST}$, and $r_{2,AT}$ are the field related earnings parameters. As a result, their relevant income values can be defined as

$$y_{2,ST} = y_0(1+r_{2,St})/(1+R)^2 \text{ for } j = ST,$$
$$y_{2,AT} = y_0(1+r_{2,AT})/(1+R)^2 \text{ for } j = AT,$$

The author assumes that $y_{2,j} > y_0,\ y_1$. These inequalities guarantee that individuals indifferent between school and work will choose to complete college if they are certain they can meet the requirements. The author also assumes that new information about earnings will arrive in period one after the first round of education decisions are made at the end of period zero.

Preferences

Utility depends on the present value of income and a taste parameter.[22] There are three types of individuals in the model, $q = 0, 1, 2$. Type-zero individuals relatively dislike school

[22]The taste parameter summarizes the nonpecuniary preferences for education programs and the job types.

and white-collar jobs. They do not receive an increase in utility from completing a degree even though they earn higher wages. Type-one people hate spending time in the field ST in school. Also, they are indifferent about spending time at work or school in major AT. If they go to college, they never pursue field ST. Type-two individuals are indifferent between fields and between school and work time. At the end of $t = 0$ (high school), individuals do not know their precise type; however, they know the probabilities of fitting into all three types, θ_q. They learn their preferred type right after the first year of college.

Educational choice decisions

At the end of period 0, an individual chooses the educational level based on expected returns to education

$$\max\Big\{y_0, V_1(\boldsymbol{h}_0, \boldsymbol{a}, \theta_q, ST_1), V_1(\boldsymbol{h}_0, \boldsymbol{a}, \theta_q, AT_1)\Big\},$$

where y_0 is the income's discounted present value if an individual enters the labour market after high school, the second and the third arguments show the values of attending ST and AT in the first year of college, where these first-year choices are represented by ST_1 and AT_1, respectively. Conditional on these choices, the values of attending college in period one are categorized as

$$V_1(\boldsymbol{h}_0, \boldsymbol{a}, \theta_q, ST_1) = \sum_{q=0}^{2} \theta_q \, \mathbb{E}(V_2(g_2, q)|\boldsymbol{h}_0, \boldsymbol{a}, ST_1), \tag{126}$$

$$V_1(\boldsymbol{h}_0, \boldsymbol{a}, \theta_q, AT_1) = \sum_{q=0}^{2} \theta_q \, \mathbb{E}(V_2(g_2, q)|\boldsymbol{h}_0, \boldsymbol{a}, AT_1). \tag{127}$$

Equations (126) and (127) show the value of attending the first year of college in the fields of ST and AT, respectively. Using the probabilities of fitting into all three types, θ_q, these equations represent the probability-weighted average of the return to education for three alternative types, $q = 0, 1, 2$. $V_2(g_2, q)$ is the value function at the end of period one for individuals who know their precise type, q. Since graduation probabilities $g2$ are stochastic, the expectation $\mathbb{E}$ is taken over the probability distribution of graduating from college at the end of the second year, g_2, conditional on initial endowments, $\boldsymbol{h}_0, \boldsymbol{a}$ and the first-year field choice of ST or AT. Equation (128) shows the value function at the end of period one for individuals who know their precise type as type-zero, $q = 0$,

$$V_2(g_2, 0) = y_1. \tag{128}$$

Based on their type, these individuals prefer to join the labour market and receive y_1 in period one. Equation (129) shows the value function at the end of period one for individuals who know their precise type as type-one, $q = 1$,

$$V_2(g_2, 1) = \max\Big\{ \underbrace{\Big[\overbrace{g_{2,AT}\ y_{2,AT}}^{\text{graduate in AT}} + \overbrace{(1 - g_{2,AT})y_1/(1 + R)}^{\text{not graduate}} \Big]}_{\text{pursue AT in the last period}}, \underbrace{y_1}_{\text{work}} \Big\}. \tag{129}$$

Type-one people hate spending time in the field ST, so they choose the maximum monetary payoffs between joining the labour market, y_1, and continuing study in humanities/social science, $\Big[g_{2,AT}\ \ y_{2,AT} + (1 - g_{2,AT})y_1/(1 + R)\Big]$, which depends on the probability of graduating in the field AT at the end of the second year, $g_{2,AT}$.

The value function at the end of period one for type-two individuals, $q = 2$, is shown by Equation (130),

$$V_2(g_2, 2) = \max\Big\{ \underbrace{\Big[\overbrace{g_{2,AT}\ y_{2,AT}}^{\text{graduate in AT}} + \overbrace{(1 - g_{2,AT})y_1/(1 + R)}^{\text{drop out}} \Big]}_{\text{study in AT}}, \underbrace{\Big[\overbrace{g_{2,ST}\ y_{2,ST}}^{\text{graduate in ST}} + \overbrace{(1 - g_{2,ST})y_1/(1 + R)}^{\text{drop out}} \Big]}_{\text{study in ST}}, \underbrace{y_1}_{\text{work}} \Big\}. \tag{130}$$

Type-two students are indifferent between fields of study and work. Therefore, they choose the maximum monetary rewards among three choices at the end of period one: joining the labour market or continuation study in period two either in AT or ST, which depends on the probability of graduations, $g_{2,AT}$ and $g_{2,ST}$.

Learning about endowments and outcomes for schooling

At the end of the first period, students may change their major or drop out of school. The choice depends on the individuals' ability, their stock of knowledge accumulated in the first year, the probability that an individual will ultimately complete a particular level of education in a specific field if they attend college, and the payoffs associated with the different educational outcomes, and the new information about their tastes for schooling. Knowing their precise types, $q = 0, 1, 2$, students choose their educational level at the end of the first period based on

$$\max\{V_2(g_2, 0), V_2(g_2, 1), V_2(g_2, 2)\}.$$

Altonji (1993) calculates *ex-ante* and *ex-post* rate of returns to starting college and finds significant differences between them.[23] This finding suggests that the option value may be important.[24]

B.7 Wiswall and Zafar (2015a)

The timing of the model

The timing of the model is to mimic that of the experiment. At the initial period $t = 0$, agents are enrolled in college but have yet to choose a specific major. They report their college major choice probabilities before they decide on the major of interest. An individual receives a utility shock for each major. After realizing these shocks, students choose a college major from one of K majors, $k = 1, \ldots, K$. Finally, students graduate at the end of the initial period.[25] In the first period following college graduation, $t = 1$, and onward, the agent makes all remaining choices, such as labour supply and marriage. In the last period, $t = T$, the individual retires.

[23] In the model, the educational decision does not depend on the *ex-post* return, computed on the earnings of graduates, who represent only a limited selection of those who enroll. Still, it depends on the *ex-ante* return, which also contemplates the probability of failure. The *ex-ante* return is computed as the probability-weighted average of the return to education in case of success or failure.

[24] The option value as defined by Weisbrod (1962) is the return that arises from going onto higher levels of education and not dropping out from the current level of study. Weisbrod is the first to point out that education has option value. Also, built on Arcidiacono (2004)'s structural model of students' sequential learning, Stange (2012) is the first to estimate and quantify the magnitude of the option value of college enrollment in the presence of uncertainty and learning about academic performance and ability. Estimates suggest that this value is substantial.

[25] Majors are (1) Business and economics, (2) Engineering and computer science, (3) Humanities and other social sciences, (4) Natural sciences and math, and (5) Never graduate/drop out.

College major choice

Individuals choose the college major that maximizes expected utility at period $t = 0$

$$V_0^* = \max\{V_{0,1}, \ldots, V_{0,k}, \ldots, V_{0,K}\}.$$

$V_{0,k}$ is the time zero utility of each college major, k, defined as:

$$V_{0,k} = \gamma_k + \alpha \ln a_k + \eta_k + \mathbb{E}\, V_{1,k}, \tag{131}$$

where γ_k is the taste or consumption value for major k at time zero.

These tastes could be for the enjoyability of coursework during college or preferences for expected non-pecuniary aspects of occupations associated with a major. A significant positive γ_k reflects a higher "switching cost" to move out of major k into an alternative major. $\ln a_k$ stands for the *perceived* ability in each major k, where $a_k > 0$ for all k. The authors expect $\alpha > 0$, reflecting that higher ability in a particular major improves performance in the major's coursework, η_k is the period zero preference shock or major-specific random shock. It could be considered a shock to the perceived ability or the taste for the major, k.

The authors assume that at college graduation, each individual has obtained a degree in a particular field $k = 1, \ldots, K$. Equation (132) shows the post-graduation utility or the lifetime utility continuation value function. It represents the discounted sum of the post-graduation utility student i expects to receive if they graduate with a major k,

$$\mathbb{E}\, V_{1,k} = \sum_{t=1}^{T} \beta^{t-1+g} \int u(X) dG(X|k,t), \tag{132}$$

where $g = \{1, 2, 3, 4\}$ is the student's years until graduation and $\beta \in (0, 1)$ is the discount rate.[26] $u(.)$ is the post-graduation utility function mapping the finite vector of post-graduation possible *events* X to utility.

Equation (132) shows that the authors get the impact of major choices not only on

[26]with g=4 (freshman), g=3 (sophomore), g=2 (junior), and g=1 (senior).

the earnings *event* but also on other *events* such as labour supply, spousal earnings, and marriage (how a given major can improve one's marriage probabilities). $G(X|k,t)$ is the elicited *beliefs* about the distribution of future events in period t, conditional on choice of major k. To approximate the life cycle utility of each major, the authors use all students' beliefs elicited directly by the survey. T is the final period of age 55.[27]

As a result, the expected post-graduation utility shown in Equation (132) can be re-written as

$$
\begin{aligned}
\mathbb{E}\, V_{1,k} = & \sum_{t=1}^{T} \beta^{t-1+g} \\
& \Bigg\{ \Pr(m_t = 0|k,t) \overbrace{\sum_{l=FT,PT,NW} \Pr(L_{1,t} = l|m_t = 0,k,t) \int \phi_1 \frac{(c_{S,1,t})^{1-\rho_1}}{1-\rho_1} dF_1(y_{FT,1,t}|k,t)}^{\text{single agent } (m_t=0) \text{ at age } t \text{ if completed major } k} \\
& + \Pr(m_t = 1|k,t) \Bigg[\underbrace{\sum_{l=FT,PT,NW} \Pr(L_{1,t} = l|m_t = 1,k,t) \int \phi_1 \frac{(c_{M,1,t})^{1-\rho_1}}{1-\rho_1} dF_1(y_{FT,1,t}|k,t)}_{\text{married agent } (m_t=1) \text{ at age } t \text{ if completed major } k} \\
& + \underbrace{\sum_{l=FT,PT,NW} \Pr(L_{2,t} = l|k,t) \int \phi_2 \frac{(c_{M,2,t})^{1-\rho_2}}{1-\rho_2} dF_2(y_{FT,2,t}|k,t)}_{\text{related to the spouse of an age } t \text{ and major } k \text{ individual}} \Bigg] \Bigg\},
\end{aligned}
$$

where $\Pr(m_t = 0|k,t)$ is the belief about the probability of being single ($m_t = 0$) at age t given major k. $\Pr(L_{1,t} = l|m_t = 0,k,t)$ is the belief about labour market status after graduation in major k and being single. The labour market status is defined by $l = FT, PT, NW$ referring to full-time, part-time, and not working, respectively.[28] $\Pr(L_{2,t} = l|k,t)$ is the belief of an individual about the labour market status of the spouse conditional on the individual's own major k and own age t (not the spouse's major or age).

$F_1(y_{FT,1,t}|k,t)$ is the individual's beliefs about their future full-time earnings conditional

[27] The authors mention that given the long horizon between college and age 55, modelling the period up to age 55 likely is sufficient for the model and omitting the higher ages has no significant consequences on approximating the utility of the college major choice.

[28] The authors define full-time status as working at least 35 hours per week and a minimum of 45 weeks during the year.

on major and age. $F_2(y_{FT,2,t}|k,t)$ is the individual's beliefs about a potential spouse's full-time earnings conditional on the individual's own major and own age. Own earnings ($q = 1$) and spousal earnings ($q = 2$) are modelled as

$$y_{q,t} = y_{FT,q,t}\mathbb{1}(FT_{q,t}) + y_{FT,q,t}\frac{20}{h_{FT,q,t}}\mathbb{1}(PT_{q,t}), \quad \text{for } q = 1, 2,$$

where earnings are defined based on the beliefs about full-time earnings, $y_{FT,1,t}$, and full-time labour supply, $h_{FT,1,t}$. $\mathbb{1}(.)$ is an indicator equal to one if the individuals believe that at age t the work will be full-time ($FT_{q,t}$) or part-time ($FT_{q,t}$). $c_{S,1,t} = y_{1,t}$ is the consumption of own when single at age t. $c_{M,1,t}$ and $c_{M,2,t}$ are the consumption of own and potential consumption of spouse, respectively. They are equal to $\frac{1}{2}(y_{1,t} + y_{2,t})$ where $y_{2,t}$ is the spouse earnings. $\rho \in (0,\infty)$ and $\phi \in (0,\infty)$ parametrize individuals' preferences over their own and their spouse's consumption. $\rho \in (0,\infty)$ is the coefficient of relative risk aversion, and $1/\rho$ is the inter-temporal elasticity of substitution (IES) for consumption.

Interestingly, Equation (132) has no optimization because the authors ask students' expectations of all relevant factors used in the equation. Using the elicited information and avoiding the optimization in the non-rational expectation framework considerably reduces the time to compute the model solution.

Main finding of the paper. The paper's main finding is that the dominant factor in choosing a college major is the unobserved heterogeneity, such as "tastes" of individuals for majors and the perceived "abilities" in those majors, explaining about 91% of the choice of a major. The rest are explained by the financial incentives (the beliefs concerning expected earnings).

How the main finding is derived?

The paper has two aspects. The first one is the estimation of the structural model. The second one is the statistical analysis of the data emerging from their experiment. The authors compare cross-sectional OLS estimates of the relationship between probabilities of major choice and "perceived" earnings with their experimental panel fixed-effects estimates

(FE). They run a log-log regression of college major beliefs on self-beliefs about their earnings using the information elicited in the first round (pre-treatment stage),

$$\Big[\ln(\pi_{k,i}) - \ln(\pi_{\tilde{k},i})\Big] = \beta_0 + \beta_1\Big[\ln(\bar{w}_{k,i}) - \ln(\bar{w}_{\tilde{k},i})\Big] + X_i\zeta + \nu_k + \underbrace{\gamma_{k,i} - \gamma_{\tilde{k},i} + \varepsilon_{k,i}}_{\psi_{k,i}}, \tag{133}$$

where $\pi_{k,i}$ is individual i's subjective probability of graduating with major k, $\bar{w}_{k,i}$ is individual i's belief about age of 30 years earnings in major k. X_i is a vector of individual-specific characteristics for which the relevant data is available, and ν_k is a major k fixed effect. $\tilde{k}$, the reference major in these regressions, is Humanities/arts. The residual error, $\psi_{k,i}$, consists of unobserved relative taste differences, $\gamma_{k,i} - \gamma_{\tilde{k},i}$, that is assumed to be time-invariant, and $\varepsilon_{k,i}$, which reflects all other residual components.

the estimates of "choice elasticity" are found to be $\hat{\beta}_1 = 1.613$, meaning that, on average, a 1% increase in self-earnings beliefs raise log odds ratio of majoring in k by almost 1.6%, which seems to be a strong positive correlation.[29] In other words, If agents' belief about their future earnings of a specific major is firm, then the probability of selecting and graduating from that major is high as well.

However, the regression can not separate taste component $\gamma_{k,i} - \gamma_{\tilde{k},i}$ from earnings component $\Big[(\ln(\bar{w}_{k,i}) - \ln(\bar{w}_{\tilde{k},i})\Big]$. If beliefs about future earnings are correlated with tastes for majors, then the estimate, $\hat{\beta}_1 = 1.613$, is biased. Therefore, authors use post-treatment information and individual (within) differences to net out the taste component in the error term, $(\gamma_{k,i} - \gamma_{\tilde{k},i})$,

$$\begin{aligned}\Big[\ln(\pi'_{k,i}) - \ln(\pi'_{\tilde{k},i})\Big] - \Big[\ln(\pi_{k,i}) - \ln(\pi_{\tilde{k},i})\Big] &= \beta_0 \\ &+ \beta_1 \,.\, \Big\{\Big[\ln(\bar{w}'_{k,i}) - \ln(\bar{w}'_{\tilde{k},i})\Big] - \Big[\ln(\bar{w}_{k,i}) - \ln(\bar{w}_{\tilde{k},i})\Big]\Big\} \\ &+ \nu_k + \varepsilon'_{k,i} + \varepsilon_{k,i},\end{aligned}$$

where $\Big[\ln(\pi'_{k,i}) - \ln(\pi'_{\tilde{k},i})\Big]$ and $\Big[\ln(\bar{w}'_{k,i}) - \ln(\bar{w}'_{\tilde{k},i})\Big]$ are the re-elicited or post-treatment information. The new estimate for the choice elasticity concerning beliefs about earnings is

[29] Table 6, p.813

$\hat{\beta}_1 = 0.146$ (FE/panel estimate) as opposed to $\hat{\beta}_1 = 1.613$ (OLS/cross-sectional estimate). Without re-eliciting the beliefs, the simple OLS/cross-sectional estimates are severely biased upwards due to the positive correlation of unobserved tastes with earnings expectations. By this regression, the paper concludes that individuals base their choices on their tastes and perceived abilities and not on the elements representing the financial returns on majors.

B.8 Castro and Coen-Pirani (2016)

The model

The proposed model is a partial equilibrium calibrated structural model of education choices in which individuals are characterized by heterogeneous learning abilities, birth cohort and taste for education. In this simple partial equilibrium model, the financial markets are frictionless, so an individual's financial resources do not constrain education choices.

The model studies the education choices of individuals in different cohorts. An agent's life starts at $a = 7$ when the individual is enrolled in their first year of school and ends at $A = 65$. All individuals are compulsory to attend school between ages 7 and 16 while their parents financially support them. So, different schooling choices are made at age 17 when agents can continue their education maximum by graduating from a four-year college or start working at age 17.

Human capital accumulation

Upon leaving school, individuals start working and continue accumulating human capital through the experience to age A, at which point the individual dies. There are four schooling levels, j, characterized by a length of study S_j during which the individual is assumed not to be able to work in the labour market: high school dropout ($j = 4, S_j = 10$), high school graduates ($j = 3, S_j = 12$), some college ($j = 2, S_j = 14$), and four-year college ($j = 1, S_j = 16$).

Human capital accumulation functions for schooling and on-the-job training differ. During the years in which the agent is enrolled in schooling level j', the human capital of an individual born in year τ with learning ability θ follows a Ben-Porath technology and accumulates according to the law of motion

$$h_{\tau a+1} = \theta h_{\tau a}^{\gamma}(x_{\tau+a}^{j'})^{\phi} + (1-\delta)h_{\tau a},$$

where $h_{\tau a}$ is the cohort τ agent's human capital at age a. γ denotes the curvature of the human capital accumulation technology, and θ represents the learning ability by age seven, which varies across cohorts.[30,31] The first year of study starts at age seven and the last possible year of study is at age 22. For example, an agent whose final schooling level is $j = 1$ (four-year college) will be enrolled in high school (school level $j' = 3$) at ages $a = 7 - 18$, and in college (school level $j' = 1$) at ages $a = 19 - 22$. The depreciation rate of human capital is shown by δ, $x_{\tau+a}^{j'}$ stands for the quality of education when attending school level j' at age a, and ϕ is the elasticity of human capital formation to school quality.

After completing education level j, an agent with learning ability θ is endowed with human capital $h_{\tau 7+S_j}(\theta)$. Starting from this point, if they begin to work, their human capital evolves exogenously over time according to a new law of motion

$$h_{\tau a}^{j}(\theta) = h_{\tau 7+S_j}^{j}(\theta)\exp\Big(\eta_1^j \underbrace{(a - S_j - 7)}_{\substack{\text{years of}\\ \text{experience}}} + \eta_2^j (a - S_j - 7)^2\Big) \quad \text{for } a = 7 + S_j, \ldots, A, \tag{134}$$

where η_1^j and η_2^j are the parameters governing the returns to experience, and $h_{\tau 7}$ stands for the initial human capital at age seven.

Preferences

Individual preferences have two components. The first component reflects consumption

[30] There is no data about individuals' learning ability. However, data on test scores of eighth-grade students were used to calibrate learning ability. These data show a progressive decline starting with the late 1940s-early 1950s cohorts and ending with the cohorts born in the early to mid-1960s.

[31] The distribution of ability, θ, conditional on cohort τ , is lognormal: $\theta \sim \mathcal{LN}(\mu_{\theta\tau}, \sigma_\theta)$

over the life cycle, while the second reflects preferences for specific education choices. At age 17, an individual must choose the level of schooling that maximizes utility. An agent in cohort τ with ability θ, and schooling preferences $\xi_i \equiv \{\xi_i^1, \xi_i^2, \xi_i^3, \xi_i^4\}$, maximizes the present discounted value of utility as age 17, defined as

$$\left[\sum_{a=17}^{A} \beta^a \ln c_{\tau a}^j\right] + \psi(\xi_i^j + \bar{\xi}^j), \tag{135}$$

where β is the constant discount factor and $c_{\tau a}^j$ denotes consumption. The random variable ξ_i^j represents individual i's preferences for schooling-level j. According to a standard type-I extreme value distribution, these preference shocks are independent across degrees j for the same individual i and are independently distributed in the population. Each person i is assumed to observe their vector of shocks at age 17 before making education and consumption choices. The parameter $\bar{\xi}^j$ captures the population's average taste (psychic rewards) for degree j. Finally, ψ captures the importance of degree-specific preferences relative to the present utility value from consumption in determining schooling choices.[32]

Budget constraint

An individual of cohort τ and learning ability θ that makes education choice j faces the following lifetime budget constraint

$$\sum_{a=17}^{A} R^{-a} c_{\tau a}^j = \sum_{a=7+S_j}^{A} R^{-a}(1-\lambda) w_{\tau+a}^j h_{\tau a}^j(\theta) - Z_\tau^j, \tag{136}$$

where R is the exogenous gross interest rate, λ is the labour income tax rate, which is assumed to be constant. $w_{\tau+a}^j$ is the skill price attached to the human capital, and Z_τ^j is the present value of tuition for any individual in cohort τ who picks schooling option j. Secondary schooling is assumed to be publicly financed so that tuition is paid only by

[32] As ψ increases, exogenous preference-related factors become more important in explaining agents' education choices relative to economic factors.

individuals attending college, $Z_\tau^4 = Z_\tau^3 = 0$. The present value of tuition Z_τ^j is defined as

$$Z_\tau^j = \sum_{a=7+S_3}^{7+S_j} R^{-a} z_{\tau+a}^j \quad \text{for } j = 1, 2,$$

where $z_{\tau+a}^j$ represents the yearly tuition for an individual in cohort τ choosing either a two- ($j = 2$) or a four-year ($j = 1$) college.

Markets are frictionless, without borrowing constraints. The budget constraint also embeds some other simplifying assumptions. First, individuals are assumed to work the same exogenous time per year, so there is no endogenous labour supply choice. Thus, the model is more appropriate for investigating the education choices of demographic groups characterized by a relatively stable labour supply over the life cycle. The authors choose a sample of male full-time and full-year workers to address this issue in the data. Second, individuals' earnings are deterministic. Third, all agents begin their lives with zero wealth, and the present value of tuition Z_τ^j is assumed to be the same for all agents in the same cohort.

Expectations for skill prices

To make their consumption and schooling decisions at age 17, individuals in each cohort τ need to formulate expectations about the path of skill prices, $\left\{w_{\tau+a}^j\right\}_{a=7+S_j}^A$, for all j that they may face during their lifetime.

The authors consider two alternative specifications for forming expectations: perfect foresight and "static" expectations. According to perfect foresight expectations, agents are assumed to know the future realization of the series of skill prices when they make choices. According to "static" expectations, agents in cohorts τ make their schooling plans by assuming that skill prices will remain constant at the level $w_{\tau+17}^j$ they observe when they make schooling decisions.

Consumption and schooling choices

Perfect credit markets deliver closed-form solutions for consumption. By maximizing the objective function, Equation (135), subject to the budget constraint, Equation (136), individuals choose a preferred level of schooling and a consumption profile over the life cycle. The discount factor is assumed to be such that $\beta R = 1$. The planned consumption level of an individual of cohort τ and learning ability θ making school choice j is then

$$c_\tau^j(\theta) = \frac{\sum_{a=7+S_j}^{A} R^{-a}(1-\lambda)\hat{w}_{\tau+a}^j h_{\tau a}^j(\theta) - Z_\tau^j}{\sum_{a=17}^{A} R^{-a}}, \tag{137}$$

where $\hat{w}_{\tau+a}^j$ denotes the expected skill price for the age a of an agent who is a member of cohort τ and has chosen education choice j at age 17. Replacing Equation (137) in Equation (135) modifies the objective function such that an individual i of ability θ and preference vector ξ_i is going to select the education levels j that solves the following problem

$$\max_j \left\{V_\tau^j(\theta) + \psi(\xi_i^j + \bar{\xi}^j)\right\}, \quad \text{where} \quad V_\tau^j(\theta) = \ln c_\tau^j(\theta) \sum_{a=17}^{A} \beta^a.$$

Individuals' ability type proportions

Type I extreme value shocks result in closed-form solutions for choice probabilities. The following equation shows the proportions of individuals of each ability type θ in cohort τ who choose schooling level j based on

$$P_\tau^j(\theta) = \frac{\exp\left(V_\tau^j(\theta)/\psi + \bar{\xi}^j\right)}{\Sigma_{k=1}^4 \exp\left(V_\tau^k(\theta)/\psi + \bar{\xi}^k\right)}. \tag{138}$$

Empirical implementation

To solve the model, three different steps are required:

First step. In the first step, the authors try to identify the evolution of skill prices (the prices of one unit of human capital for each educational category). There is no data available for this variable. However, the authors observe the hourly wages in the data, consisting of two unobservable parts. The first part is the skill price, and the second is the quantity of human capital endogenous in the model.

To infer the evolution of skill prices from the earnings data, the authors exploit variation over time in the average earnings of individuals of a given schooling group and cohort to identify the evolution of skill prices and partially identify the returns to experience parameters. This approach calculates the growth rates of skill prices over time but not their initial values, which need to be calibrated.

To compute the growth rates of skill prices, let $w_t^j \bar{h}_{\tau t}^j$ represent the average earnings in period t of workers who belong to cohort τ and make schooling choice j. Taking the logarithm of $w_t^j \bar{h}_{\tau t}^j$ and using equation (134) yields the following expression

$$\ln w_t^j \bar{h}_{\tau t}^j = \ln w_t^j + \ln \mathbb{E}\left[h_{\tau 7+S_j}^j(\theta)|\tau, j\right] + \eta_1^j \underbrace{(\overbrace{t-\tau}^{\text{age}} - S_j - 7)}_{\text{experience}} + \eta_2^j (t-\tau-S_j-7)^2. \quad (139)$$

Taking the first difference (over time) of equation (139), the growth rate of average earnings for individuals in cohort τ can be decomposed as

$$\ln\left\{\frac{w_{t+1}^j \bar{h}_{\tau t+1}^j}{w_t^j \bar{h}_{\tau t}^j}\right\} = \ln\left\{\frac{w_{t+1}^j}{w_t^j}\right\} + \eta_1^j + \eta_2^j\Big(2(t-\tau-S_j-7)+1\Big). \quad (140)$$

The first term on the right-hand side of Equation (140), $\ln\left\{\frac{w_{t+1}^j}{w_t^j}\right\}$, is the growth rate of skill prices, and the other two terms represent the growth rate of human capital due to the accumulation of experience.[33] The growth rate of average earnings between periods t and $t+1$ for a given cohort τ of agents is assumed to be measured with error

$$e_{\tau t+1}^j = \ln\left\{\frac{w_{t+1}^j \bar{h}_{\tau t+1}^j}{w_t^j \bar{h}_{\tau t}^j}\right\} + u_{\tau t+1}^j, \quad (141)$$

where $e_{\tau t+1}^j$ denotes the observed growth rate and $u_{\tau t+1}^j$ is the classical measurement error. To obtain a smooth profile of skill prices, $\ln\left\{\frac{w_{t+1}^j}{w_t^j}\right\}$, it is specified as a cubic polynomial in

[33]The log of average human capital at the end of school-level j, $\ln \mathbb{E}\left[h_{\tau 7+S_j}^j(\theta)|\tau, j\right]$, cancels out because it does not depend on time.

time

$$\ln\left\{\frac{w^j_{t+1}}{w^j_t}\right\} = \alpha^j_0 + \alpha^j_1 t + \alpha^j_2 t^2 + \alpha^j_3 t^3. \tag{142}$$

Replacing Equation (142) in Equation (140) then substituting it into Equation (141) yields the regression equation to be estimated

$$e^j_{\tau t+1} = \eta^j_1 + \alpha^j_0 + \alpha^j_1 t + \alpha^j_2 t^2 + \alpha^j_3 t^3 + \eta^j_2\Big((t-\tau-S_j-7)+1\Big) + u^j_{\tau t+1}, \tag{143}$$

where α^j_k, for $k = 0 - 3$, are the parameters of the cubic polynomial, and the first year in the data (1949) corresponds to $t = 0$. In Equation (143), η^j_1 is not separately identified from the constant term α^j_0. It will be identified by requiring the model to match some other moments. The remaining parameters can instead be identified and estimated using ordinary least squares.

Second step. In this step, the authors set a priori some parameters of the model based on available evidence and normalization $\Big(A,\, R,\, \beta,\, \lambda,\, \phi,\, \gamma,\, \delta,\, \bar{\xi}^4,\, \mu_{\theta 1932}\Big)$, where $\mu_{\theta 1932}$ stands for the average learning ability of individuals in the 1932 cohort, and $\bar{\xi}^4$ represents the psychic cost of high school dropouts.

Third step. In the last step, the authors calibrate the remaining parameters: $\Big(\sigma_\theta, \psi, \{\bar{\xi}^j\}^3_{j=1}, \{w^j_0\}^4_{j=1}, \{\eta^j_1\}^4_{j=1}\Big)$ plus an additional parameter, $\mu_{\theta 1963}$, that represents average learning ability of individuals in the 1963 cohort. To calibrate these 14 parameters, the authors focus on 16 moments, such as the share of workers in the 1932 and 1972 cohorts with different levels of education, college and some college earnings premiums, etc.

By matching some moments, the authors force the model to correctly reproduce the endpoints and several levels. Then the authors are interested to see the evolution of educational attainment between 1932 and 1972 as the paper's primary goal.